sustainability

Systematic Review

Can Digital Twin Technology Enhance Supply-Chain Resilience? A Systematic Literature Review

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Abstract

Digital twin technology (DTT) creates a virtual replica of a physical object, system, or process and uses real-time data to support monitoring, analysis, and control. Although DTT is increasingly discussed as a means to enhance supply-chain resilience, prior evidence is fragmented and lacks an integrated view across disruption stages. This study conducts a systematic literature review of 89 peer-reviewed articles on DTT and supply-chain resilience, applying relevance-based screening to retain studies with substantive theoretical and practical implications. The review indicates that DTT applications for resilience are emergent but gaining momentum, and that their contribution differs by resilience stage. Specifically, DTT capabilities support preparedness through enhanced visibility, risk sensing, and scenario testing; resistance through real-time monitoring, early warning, and evaluation of mitigation options; rebound through response coordination, recovery planning, and adaptive reconfiguration; and growth through post-disruption learning and network redesign. The synthesis also identifies key barriers to adoption, including data quality limitations, high implementation costs, shortages of specialised skills, and governance challenges, and suggests that integration with complementary digital technologies often enables more advanced functionality. Overall, the study provides a stage-based consolidation of DTT capabilities, benefits, and barriers to guide research and managerial deployment.

Keywords: digital twin; supply-chain resilience; digital supply-chain twin; systematic literature review

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1. Introduction

Supply chains increasingly operate under conditions of volatility and disruption, driven by intensifying global competition, shifting customer expectations, and shocks arising from natural and geopolitical events. These pressures have made supply-chain resilience (SCR) a strategic priority, as firms must anticipate disruptions, maintain performance during events, and recover quickly while adapting to longer term change.

In response, supply-chain digitalisation has accelerated, with organisations adopting data-driven technologies to improve visibility, prediction, and coordination across networks. Within this broader trend, digital twin technology (DTT) has attracted growing attention as a way to represent and analyse complex systems through digital models linked to operational data. Existing reviews summarise key DTT concepts, enabling technologies, and industrial applications, highlighting the potential of digital twins as an integrative approach for monitoring and analysis across settings [1]. DTT is also closely associated

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with Industry 4.0 and cyber physical production systems, where digital representations support improved planning and control in connected operational environments [2].

Despite this growth in interest, research relevant to DTT and SCR remains uneven in both focus and depth. A method-oriented stream demonstrates how digital twin enhanced approaches can support disruption management in operational settings, for example through shop floor level decision support during disturbances [3]. A foundational conceptual stream emphasises the simulation aspect of digital twins as a basis for analysing system behaviour and exploring alternative decisions under uncertainty [4]. In addition, established definitions describe DTTs as virtual information constructs representing physical products or systems at multiple levels of detail, enabling insights that would otherwise require direct inspection of the physical counterpart [5]. More broadly, DTT is increasingly discussed from operations management and Industry 4.0 perspectives, which highlights interdisciplinary opportunities but also variation in how DTT is conceptualised and applied across contexts [6]. Sector-oriented studies further illustrate how digital representations support traceability and asset governance in healthcare-related supply networks, indicating the breadth of application domains where data integration and digital representations can enhance visibility and control [7].

This review identifies three gaps that limit cumulative understanding of DTT in supply-chain resilience. First, many studies describe disruption-related benefits but do not consistently specify the underlying DTT capabilities as mechanisms, which makes it difficult to compare findings and explain how value is generated for resilience. Second, resilience is often discussed in general terms, with limited clarity on when DTT contributes before, during, and after disruptions, and how capabilities differ across these stages. Third, adoption-oriented evidence remains fragmented across sectors and study types, limiting understanding of additional benefits beyond resilience and the barriers that constrain implementation and scaling. These gaps persist even though enabling technologies such as IoT, big data analytics, artificial intelligence, and cloud and edge computing are increasingly recognised as making advanced modelling and continuous data integration more feasible in supply-chain contexts [8].

Emerging studies begin to address parts of this agenda, for example by discussing DTT's value for risk management and product lifecycle decision making [9] and by examining sector-specific benefits in contexts such as pharmaceutical and horticultural supply chains [10,11]. However, a systematic consolidation that connects DTT capabilities to resilience needs across disruption stages remains limited.

Prior reviews in digital supply chains, Industry 4.0, and supply-chain risk and resilience provide useful overviews of enabling technologies and general drivers or barriers. In contrast, this review contributes a stage-based synthesis that maps DTT capabilities onto four resilience stages, preparedness, resistance, rebound, and growth, and makes the coding logic explicit. We distinguish DTT capabilities from performance benefits and adoption barriers, and we transparently separate the broader evidence base from the subset of studies that provide sufficient stage relevant detail for classification. Conceptually, introducing the post recovery growth stage highlights learning, redesign, and capability accumulation mechanisms that are not fully captured in common three stage resilience framings. As a result, the review provides a capability by stage synthesis that clarifies what is well supported, what is contingent, and where empirical evidence remains limited.

Accordingly, this paper synthesises the extant literature and provides a systematic understanding of (i) where DTT has been implemented for SCR to date, (ii) the additional benefits achieved, and (iii) the impact and challenges associated with adoption. To achieve these objectives, we address the following research questions:

RQ1: *What are the main DTT capabilities associated with enhanced supply-chain resilience? Do these vary across different resilience stages?*

RQ2: *What are the additional benefits achieved through DTT adoption?*

RQ3: *What are the challenges/barriers when adopting DTT for enhanced resilience?*

The structure of this article is as follows. Section 2 introduces DTT and its relevance to supply-chain contexts. Section 3 outlines the systematic literature review methodology. Section 4 presents the findings, including the stage-based synthesis of DTT capabilities and the reported benefits and barriers. Section 5 discusses implications and boundary conditions. Section 6 discusses potential directions for future research. Section 7 is the conclusion.

2. Concept Development

2.1. Digital Twin Technology

A digital twin refers to a virtual representation or counterpart of a physical entity, system, or process; it can be also called a digital mirror, virtual twin, or digital shadow [12]. Since 2003, various definitions of a digital twin have been proposed in the literature, and Table 1 captures the evolution of the digital twin concept. Viewed as a real-time data or simulation model that acquires data from the field and triggers the operation of physical objects, it is possible that through DTT the entire product lifecycle can be understood, learned, and revealed [13].

Table 1. The evolution of digital twins' definition.

Year.	Definition of Digital Twin	Key Points
2010	Digital twin is a digital item used to generate a characterised twin for every user based on preset configuration and "pasting" dimensional picture.	Virtual replica
2013	Digital twin is an ambitious vision to emulate the actual structure of an aircraft subject to the for near real-time prediction of structural health, maintenance planning, etc., based on high-fidelity characteristics.	High-fidelity
2016	The digital twin is a set of virtual information constructs that fully describes a potential or actual physical manufactured product from the micro atomic level to the macro geometrical level. At its optimum, any information that could be obtained from inspecting a physical manufactured product can be obtained from its digital twin.	Virtual information description
2017	A digital twin is a virtual model that represents a physical object, process, or system. It can be used to simulate and optimise designs, as well as monitor and improve the performance of products and production processes.	Virtual model
2018	Digital twin technology can support smart manufacturing by providing a virtual representation of the physical manufacturing environment, including machines, equipment, and production processes.	Virtual representation
2019	Digital twins can be used to create a virtual representation of a physical system or service, allowing for real-time monitoring, analysis, and optimisation.	Real-time monitoring
2020	The digital twin is a dynamic virtual replica of a physical object or system that can be used for various purposes such as simulation, optimisation, and monitoring.	Dynamic virtual replica
2022	A digital twin develops an innovation management model based on the Viable System Model to cope with any potential future environment based on internal organisational capabilities.	Dynamic virtual system

Furthermore, a digital twin can be seen as both a concept and a technological application. It represents a conceptual framework and a technological approach that involves creating a digital replica or representation of a physical object, system, or process [4,5]. In other words, a digital twin is a virtual counterpart that mirrors the real-world entity in a digital space [13]. At its core, the digital twin concept signifies a departure from traditional modes of systems representation. It embodies the idea that a virtual replica, synchronised in real-time with its physical counterpart, can serve as an analytical and predictive tool [14]. This conceptual framework stresses the interdependence of the physical and digital domains, offering a comprehensive understanding of complex systems and facilitating informed decision-making.

From a technological perspective, the digital twin encompasses a synergistic integration of multiple technological components, rather than a single monolithic technology [15]. Building a digital twin requires a combination of technologies that work together to create a virtual representation of a physical object or system. These technologies can be broadly categorised into four main areas:

- Data acquisition and transmission: Typically, Internet of things (IoT) devices or sensors are embedded in the physical object or system to capture real-time data. Such data typically are transmitted via wireless network to a digital infrastructure such as cloud computing [12].
- Data storage and processing: Cloud and edge computing are common approaches for storing, managing and processing data generated by IoT devices or sensors. Big data analytics can be utilised to extract useful insights from the data.
- Modelling and simulation: A range of tools such as 3D modelling and simulation can be deployed to simulate the physical behaviour of the target object or system and enable what-if scenario analysis [16,17]. More recently, the use of machine learning and AI is increasingly utilised to predict the future behaviour of the target systems.
- Visualisation and Interaction: To allow users to interact and interrogate with the digital twin system, tools such as dashboards and augmented reality are typically utilised to provide intuitive interfaces for visualising data and monitoring system performance.

In summary, the term "digital twin" encompasses both a conceptual framework and a complex integration of technologies. Conceptually, it indicates the creation of a virtual counterpart that mirrors the physical object, with an emphasis on real-time monitoring and decision-making. Building a digital twin is related to the coordination among multiple components: data acquisition through IoT devices, data storage and processing through cloud and edge computing, modelling establishment tools, and user interface visualisation. These multi-dimension approaches can help to thoroughly understand complex systems and demonstrate the transformative power of the digital twin concept in various domains.

2.2. Hierarchical Structure of DTT in Supply Chains

With supply chains increasingly being viewed as complex adaptive systems, the DTT can help understand the multitude of processes that govern them, including material and information circulation and product design, machine simulation, manufacturing, construction, transportation, warehousing management, and broader supply-chain applications. Figure 1 illustrates the relevance of DTT when managing supply chains. A network level might refer to a multi-stakeholder value network, from warehouses, different malls or shopping centers to customers. At site level, these twins might represent, for example, warehouses or production facilities. In the realm of material circulation, for example, ref. [15] posited that DTT fosters opportunities for re-engineering value networks by enhancing their circularity, either by transforming materials and products through circular design or by operating waste value networks. Furthermore, a perception-monitoring-feedback framework was introduced based on digital twin machine simulation, addressing critical issues such as slow simulation speeds, insufficient tool collision data, and suboptimal monitoring outcomes.

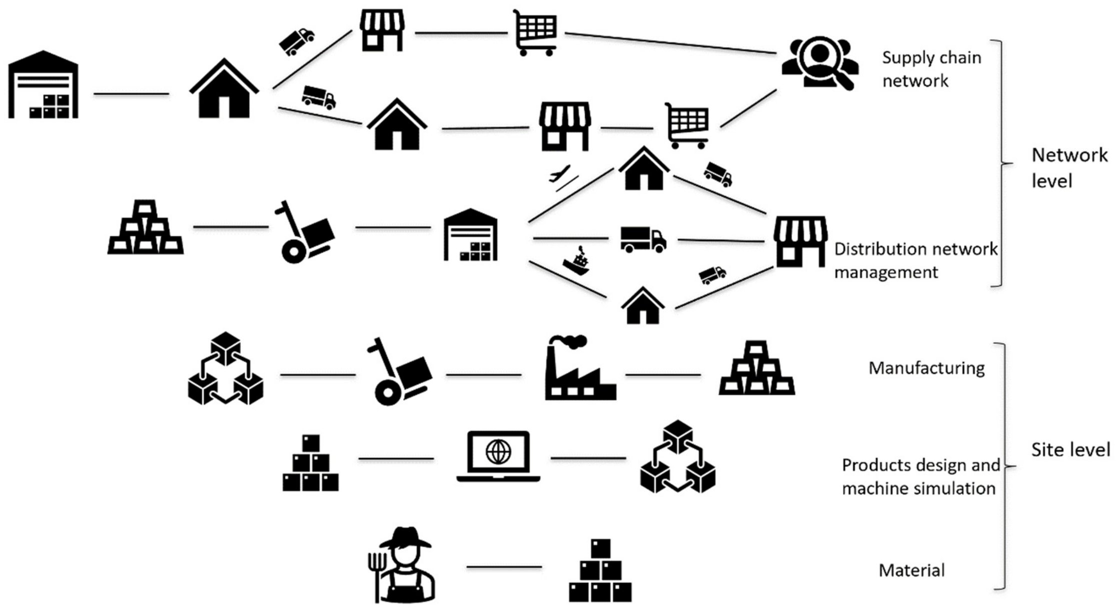

Figure 1. Hierarchical structure of DTT in supply chain. Source: Author.

Likewise, the resilience and efficiency of some supply chains in the manufacturing sector were notably improved during the COVID-19 crisis through the application of DTT [18]. As such, ref. [18] emphasised that digital twins significantly contributed to improving the effectiveness and efficiency of the construction of urban public facilities. The COVID-19 pandemic has also exerted profound impacts on supply-chain elements, including transportation, warehousing, and delivery. This has prompted scholars to further explore the integration of DTT within risk management frameworks [19–21].

Ref. [22] distinguished DTT applied in the supply chain to two primary levels: network level and site level, which rely on whether an entire value network is examined, or merely a part of network. Network level relates to a multi-stakeholder value network, focusing on the interwoven links between businesses like suppliers, manufacturers, and retailers. This can represent the entire value network, which includes network management and transportation. Site level refers to logistics sites like warehouses, production facilities, and manufacturing.

However, while numerous scholarly articles have investigated the general benefits of DTT across various industries, as well as the more specific ones associated with its contribution to enhance supply-chain resilience, the knowledge is fragmented and needs consolidating. This is also the case for discussions regarding the potential risks and challenges associated with implementing DTT in supply chains for enhanced resilience. Answering these questions is crucial for advancing scholarly understanding, informing practical implementation strategies, and fostering the effective utilisation of DTT to enhance supply-chain resilience.

2.3. Supply-Chain Resilience (SCR)

As the COVID-19 pandemic spread globally over the last few years, supply chain resilience has emerged as a major research focus. Supply chains faced significant disruptions during the pandemic, making supply chain risk management and resilience topics of increasing attention in research.

Supply-chain resilience is defined as the adaptive capability of supply chain to be prepared for unexpected events and respond and recover to its original status [23]. Hence, ref. [21] built up the foundational framework for resilient supply chains and highlighted visibility, flexibility, and velocity as crucial components. Their research emphasises the necessity of incorporating resilience into supply-chain design to ensure quick responses to disruptions. ref. [1] explored the drivers of SCR, categorised across three major resilience stages: preparedness, resistance, and rebound, shown as Figure 2. The preparedness-related SCR drivers enable a firm to prepare for an unforeseen incident before its occurrence; resistance is the ability to resist disruption and minimise the losses; rebound is the ability of a firm to recover from the disruption or interruption and back to the healthy operations or better way [24]. Although, ref. [22] conceptualise resilience through these three stages, later reviews and conceptual frameworks extend this process view by introducing a fourth growth stage, which emphasises learning and improvement beyond recovery and the transition towards a new and more desirable post-disruption state [1–3].

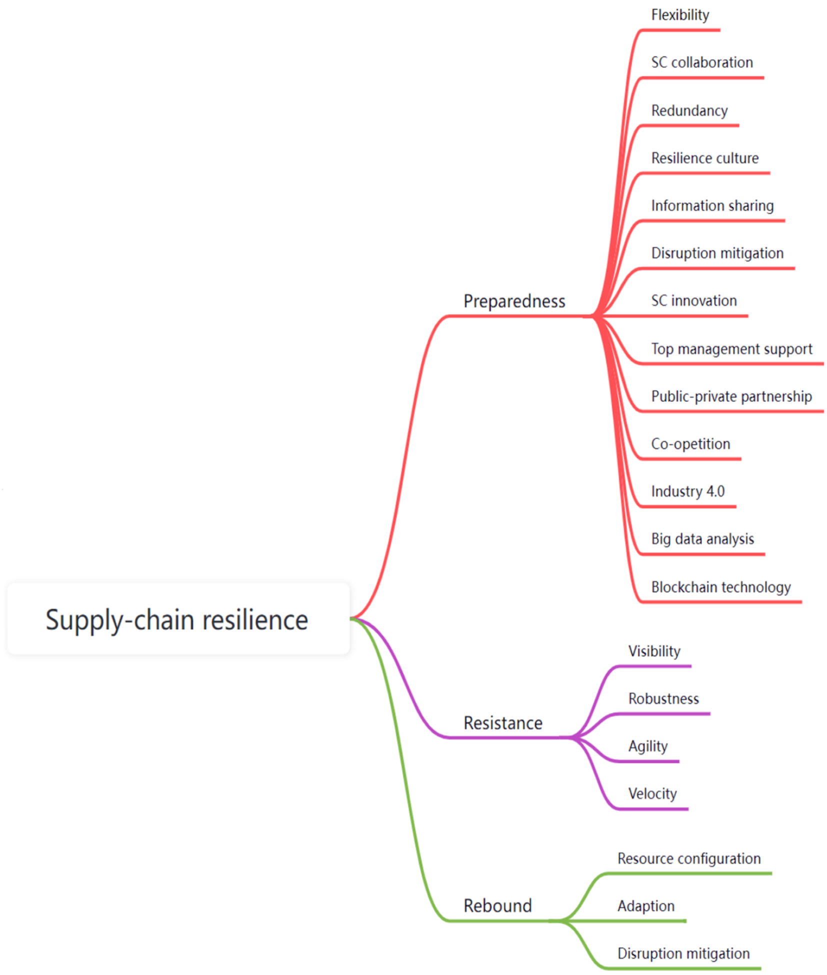

Figure 2. Supply-chain resilience capabilities. Adapt from [24].

2.3.1. Preparedness Stage

The preparedness stage of supply-chain resilience concerns the capacity of organisations to anticipate, plan for, and minimise the impact of potential disruptions before they occur. It represents a proactive approach that combines foresight with structured planning to build readiness for uncertain events. Ref. [25] emphasise that preparedness forms the foundation of resilience by allowing firms to identify vulnerabilities and implement preventive strategies in advance. Ref. [24] similarly describe preparedness, often referred to as readiness, as one of the most critical antecedents of resilient performance because it enables rapid and coordinated responses once disruptions arise. Empirical studies highlight that well-prepared supply chains use forecasting tools, scenario simulations, and contingency planning to improve response speed and continuity during crises [26]. Recent work also links digitalisation to preparedness, showing that technologies such as predictive analytics, data integration platforms, and digital twins strengthen early-warning capabilities by improving visibility and decision-making accuracy [27,28]. Policy reviews from the OECD further underline preparedness as a public and private priority, arguing that organisations capable of proactive planning and cross-sector collaboration recover more quickly and sustain competitiveness after disruptions. Together, these studies position preparedness as an essential stage in the resilience process where anticipation and prevention form the basis for effective resistance and recovery.

2.3.2. Resistance Stage

The resistance stage of supply-chain resilience refers to the ability of a supply chain to withstand disruption and maintain functionality once a disturbance has been detected. Ref. [29] define resistance as the capability to resist or neutralise the negative effects of both foreseen and unforeseen disruptions, ensuring the continuity of operations. This stage has been widely recognised as the point at which resilience is tested under real conditions, where organisations must absorb shocks without major performance degradation [29]. Scholars describe resistance as being supported by key capabilities such as flexibility, redundancy, collaboration, and robustness, which together enable firms to stabilise operations during crises [3,30]. Research shows that these capabilities allow supply chains to localise problems quickly, redistribute resources, and sustain service levels when unexpected events occur [31]. Digital transformation has recently added a new dimension to resistance, with technologies such as digital twins, real-time analytics, and IoT-based monitoring systems enhancing visibility and responsiveness during disruption [32]. These tools provide early situational awareness and enable data-driven decisions that minimise downtime and prevent escalation. Overall, the literature portrays resistance as the operational core of resilience, translating preparedness into tangible action and determining how effectively a supply chain endures the immediate impact of disruption.

2.3.3. Rebound Stage

The rebound stage of supply-chain resilience concerns the ability of a system to recover from disruption and restore or even improve its operational performance. Ref. [24] define this stage as the capacity to adapt and return to normal functioning after a disturbance, emphasising that effective recovery distinguishes resilient supply chains from fragile ones. The rebound phase is not limited to returning to the status quo but often involves transformation and learning that strengthen future resilience [23]. Scholars highlight that recovery speed, adaptive reconfiguration, and the ability to capture lessons from past disruptions are central indicators of this stage [1,31]. Recent studies show that digital technologies play a pivotal role in accelerating recovery processes. Digital twins, for example, enable organisations to simulate alternative recovery paths, optimise resource allocation, and support decision-making during the transition back to stability [32]. Likewise, advanced analytics and cloud-based collaboration tools enhance post-disruption coordination among partners, allowing faster realignment of production, distribution, and inventory systems [33]. Overall, the rebound stage represents the learning-oriented dimension of resilience, where organisations transform disruption experiences into improved capabilities, ensuring long-term adaptability and competitiveness.

2.3.4. Growth Stage

The growth stage represents the most advanced dimension of supply-chain resilience, where organisations not only recover from disruption but emerge stronger and more capable than before. Scholars describe this stage as the transformative phase that extends beyond restoration and focuses on long-term improvement in performance, strategy, and learning [1,30,34]. Ref. [34] were among the first to suggest that resilience should not end with recovery but should also involve development and renewal. Building on this idea, ref. [1] defines growth as the ability of a supply chain to exceed its pre-disruption state and achieve a new and improved level of functioning. In this stage, disruptions are viewed as catalysts for innovation, encouraging firms to reconfigure networks, redesign processes, and strengthen collaboration across the supply base. Studies have shown that organisations capable of growth after disruption often use reflective learning and knowledge sharing to enhance their adaptive capacity [30,35]. This process transforms past vulnerabilities into future strengths, allowing firms to embed resilience as a source of competitive advantage. The growth stage therefore represents the culmination of resilience maturity, where continuous learning and strategic adaptation enable supply chains not merely to survive turbulence but to evolve through it.

2.4. Digital Twins Capabilities Across Supply-Chain Resilience

Digital twin technology is particularly relevant to supply-chain resilience because its core characteristics align with the main informational and decision requirements that arise before, during, and after disruptions. In Section 2.1, digital twins were defined as data-connected virtual counterparts that mirror physical entities and can support real-time monitoring, analysis, and decision making through integrated data acquisition, processing, modelling, and visualisation components [4,5,12–15]. In Section 2.3, supply-chain resilience was defined as an adaptive capability involving preparedness, resistance, rebound, and in extended views, growth beyond recovery [23,24].

This alignment can be explained using a stage perspective. During preparedness, resilience requires early visibility, anticipation, and planning. Digital twins support these needs through end-to-end visibility, predictive insight, and scenario testing enabled by modelling and simulation, including what-if analysis [16,17,24]. During resistance, resilience requires rapid detection of disturbances and coordinated operational control to maintain acceptable performance. Digital twins can strengthen resistance by integrating real-time data streams and providing situational awareness and decision support that improve responsiveness during disruption [12,14,23]. During rebound, resilience requires recovery planning and resource reconfiguration to restore performance. Digital twins can support rebound by enabling simulation-based evaluation of recovery options and supporting more informed allocation and scheduling decisions during restoration [16,17,23,24]. Finally, growth emphasises learning and improvement beyond recovery, where insights from digital representations and disruption analysis can inform redesign of structures, processes, and policies over time [24].

Therefore, integrating the digital twin and supply-chain resilience literature is necessary for a systematic review. While prior studies discuss digital twins across supply-chain contexts and highlight their potential value, the knowledge remains fragmented in terms of which digital twin capabilities matter, when they matter across resilience stages, and what benefits and barriers are consistently reported [18–21]. This review addresses that need by consolidating evidence and mapping digital twin capabilities to preparedness, resistance, rebound, and growth.

3. Methodology

A systematic literature review (SLR) methodology was employed to conduct a comprehensive analysis of extant literature and provide an overview of how DTT is currently applied in supply chains for enhanced resilience. The aim is to consolidate current knowledge in the subject and establish a foundation for future research [36]. This approach involves filtering and selecting articles most relevant to the research topic, ensuring a focused exploration of the subject.

An SLR distinguishes itself from narrative reviews by employing explicit methods to perform a comprehensive literature search and critically appraise individual studies. The focus is on a rigorous, replicable scientific process [17,37]. Furthermore, an SLR is a methodology that identifies existing relevant studies, selects and assesses their contributions, analyses and synthesises data, and presents the findings in a manner that enables clear conclusions about what is known and what remains unknown [38]. Consistent with the approach proposed by [39], we followed the literature review process of planning the review, review execution, and reporting of the review (see Figure 3). In addition, the reporting of the search and screening process follows PRISMA criteria (relevance, methodological transparency, and institutional credibility) and are excluded if they are promotional or methodologically unclear. The study identification and selection steps are summarised in the PRISMA flow diagram (Figure 4).

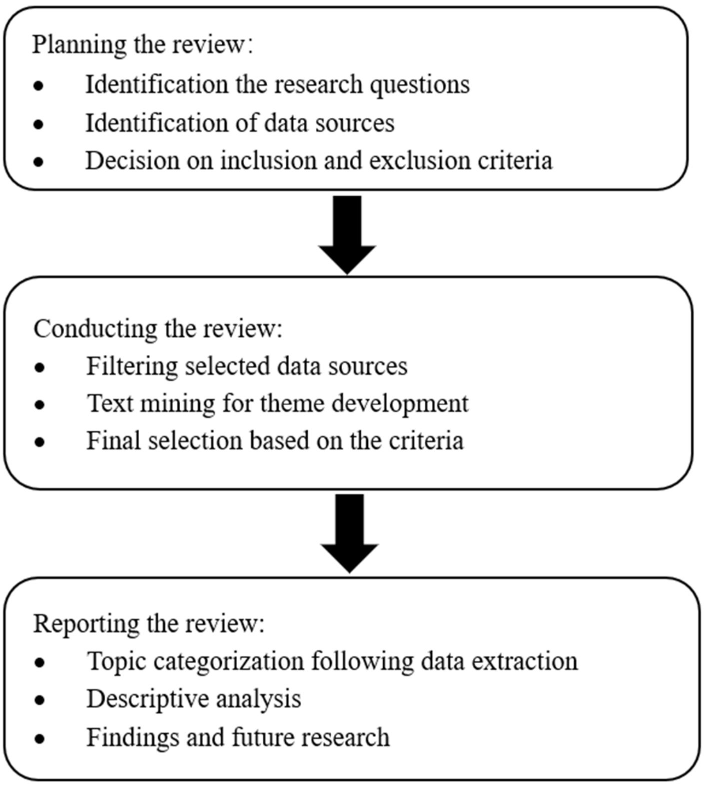

Figure 3. Methodology framework. Source: adapted from [40].

3.1. Planning the Review

Two bibliographic databases, Scopus and Web of Science (WoS), were selected as the primary sources to ensure broad coverage of peer reviewed literature and access to citation links. Scopus provides extensive indexing of abstracts and citations in peer reviewed outlets [41], and WoS offers complementary coverage and citation tracing. Google Scholar was initially explored to assess potential incremental coverage. It yielded 117 records; however, after deduplication using DOI matching and title and year checks, these records did not provide additional unique eligible studies beyond Scopus and WoS. Therefore, Google Scholar was not used as a primary database for the final review. The search strategy, field settings, and inclusion and exclusion criteria are summarised in Table 2.

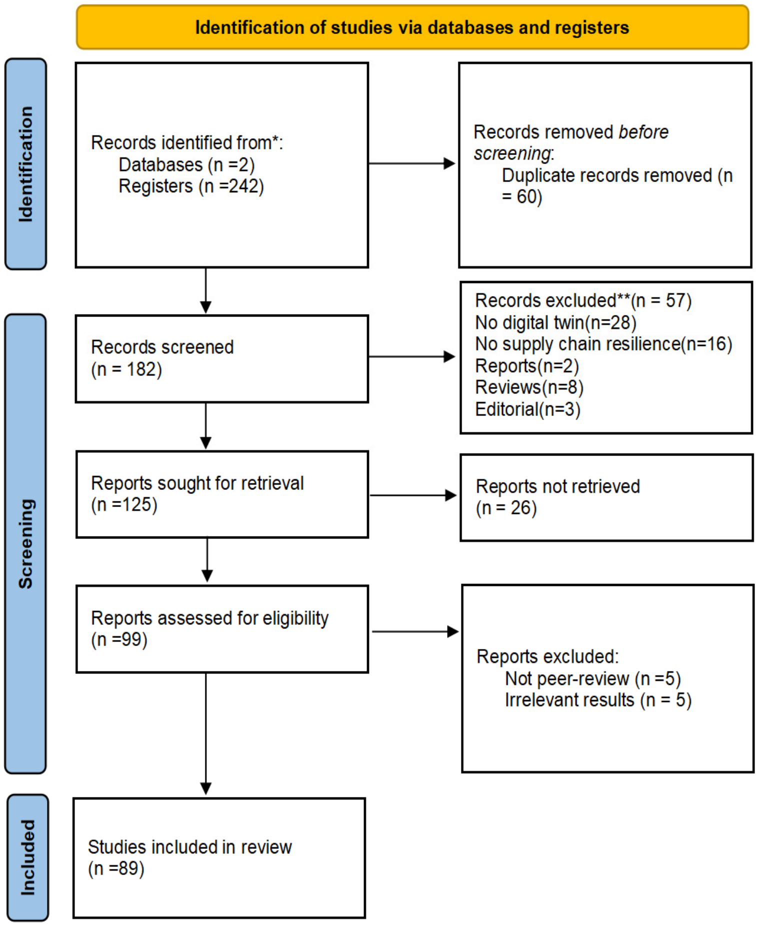

Figure 4. Paper search and selection process.

Table 2. A summarisation of the whole SLR methodology with the filters and the inclusion criteria.

Criterion	Description
Database	Web of Science and Scopus
Topics	WoS (TS): TS = ("digital twin" OR "digital shadow" OR "virtual twin") AND TS = ("supply chain resilience" OR "supply chain uncertainty" OR "supply chain disruption" OR "robust supply chain") Scopus (TITLE-ABS-KEY): TITLE-ABS-KEY ("digital twin" OR "digital shadow" OR "virtual twin") AND TITLE-ABS-KEY("supply chain resilience" OR "supply chain uncertainty" OR "supply chain disruption" OR "robust supply chain")
Inclusion	(1) peer-reviewed and in English; (2) substantively addressed DTT in a supply-chain context; and (3) explicitly examined SCR/disruption/risk issues or provided extractable relevant resilience implications.
Exclusion	(1) grey literature (theses/dissertations, reports, policy/government documents, white papers); (2) were non-English; (3) had no accessible full text; (4) were conference reviews/editorials; and (5) mentioned DTT or SCR only in passing without substantive focus.
Search date	31 May 2025

To align with PRISMA, eligibility criteria were specified prior to screening. Studies were eligible if they were peer reviewed and in English, addressed DTT substantively in a supply-chain context, and explicitly examined supply-chain resilience, disruption, risk, or uncertainty, or provided extractable implications relevant to resilience. Studies were excluded if they were grey literature (for example theses and dissertations, reports, policy or government documents, and white papers), non-English, conference reviews, editorials, or letters, lacked accessible full text, or mentioned DTT or SCR only in passing without substantive focus. Following study selection, descriptive analysis was conducted to provide an overview of the field, and content analysis was used to address the research questions and derive implications and future research directions.

3.2. Conducting the Review

The purpose of this article is to explore the application of digital twin in supply-chain resilience. Therefore, two groups of keywords searches, representing each topic, were created to reflect the relevant research as follows:

- DTT-related keywords group: "digital twin" OR "digital shadow" OR "virtual twin"
- SCR-related keywords group: "supply chain resilience" OR "supply chain uncertainty" OR "supply chain disruption" OR "robust supply chain".

No publication-year restrictions were imposed. Records were limited to English-language and peer-reviewed publications. The initial search was executed in November 2023, and an updated search was executed in May 2025; the review therefore includes studies indexed in the databases up to 31 May 2025.

The combined searches yielded 242 records (Scopus 125, WoS 117). All records were exported to Mendeley for aggregation and deduplication using DOI matching and title and year checks. After removing duplicates, 182 unique records remained. Screening followed PRISMA aligned stages, including title screening, abstract and keyword screening, and full text eligibility assessment, as summarised in Figure 4 and Table 2. During full text assessment, 26 records could not be retrieved and were therefore excluded. Additional exclusions were made for studies that were not peer reviewed or did not provide relevant results for the objectives of this review, resulting in a final set of 89 articles retained for synthesis. A formal quality appraisal was conducted using a light-touch checklist; accordingly, conclusions are phrased cautiously where evidence is primarily conceptual or where resilience impacts are implied rather than directly measured. To minimise bias, each study was independently evaluated by two researchers.

3.3. Results of Included Studies

Below, we present the findings from the 89 included studies, drawing on the study information summarised in Table 3, including reference number, publication type, research design, stage coding and primary stage, and key digital twin characteristics. The results are organised around the four resilience stages of preparedness, resistance, rebound, and growth, and we highlight how the evidence varies by study design and the reported digital twin characteristics across these stages.

Table 3. Main characteristics of the studies included in the systematic review.

Ref. No.	Author (s), Year	Pub. Type	Research Design	Stage-Coded? (Y/N)	Primary Stage (If Y)	Key DT Characteristics (1–3 Tags)	Notes
[1]	Liu, M (2021)	Journal article	Empirical research—Statistical (empirical)	N		DT applications	

Table 3. *Cont.*

Ref. No.	Author (s), Year	Pub. Type	Research Design	Stage-Coded? (Y/N)	Primary Stage (If Y)	Key DT Characteristics (1–3 Tags)	Notes
[2]	Uhlemann, T (2017)	Journal article	Empirical research—Statistical (empirical)	N		DT applications	
[3]	Hong Lim, K (2021)	Conference paper	Analytical research—Statistical (analytical)	N		DT architecture/deployment	
[4]	Boschert, S (2016)	Book/Book chapter	Empirical research—Case study	N		simulation/what-if	
[5]	Grieves, M (2016)	Book/Book chapter	Analytical research—Statistical (analytical)	N		AI/predictive analytics, DT architecture/deployment	
[6]	Ivanov, D (2020)	Journal article	Analytical research—Statistical (analytical)	N		DT applications	
[7]	Gebreab, S (2022)	Journal article	Analytical research—Statistical (analytical)	N		real-time visibility, traceability & trust	
[8]	Defraeye, T (2021)	Journal article	Analytical research—Statistical (analytical)	N		DT applications	
[9]	Attaran, M (2023)	Journal article	Empirical research—Case study	N		DT applications	
[10]	Negri, E (2020)	Journal article	Empirical research—Case study	N		DT architecture/deployment	
[11]	Schleich, B (2017)	Journal article	Analytical research—Statistical (analytical)	N		DT applications	
[12]	Sacks, R (2020)	Journal article	Analytical research—Statistical (analytical)	N		DT applications	
[13]	Büyüközkan, G (2018)	Journal article	Empirical research—Case study	N		DT architecture/deployment	
[14]	Bhandal, R (2022)	Journal article	Analytical research—Statistical (analytical)	Y	Preparedness	DT applications	
[15]	Kalaboukas, K (2023)	Journal article	Empirical research—Case study	Y		DT architecture/deployment	
[16]	Shen, W (2020)	Journal article	Analytical research—Statistical (analytical)	N		DT applications	
[18]	Deiva Ganesh, A (2022)	Journal article	Analytical research—Statistical (analytical)	N		real-time visibility, AI/predictive analytics, DT architecture/deployment	
[19]	Gerlach, B (2021)	Journal article	Empirical research—Case study	N		DT applications	
[24]	Aryatwijuka, W (2024)	Journal article	Empirical research—Statistical (empirical)	N		AI/predictive analytics	

Table 3. *Cont.*

Ref. No.	Author (s), Year	Pub. Type	Research Design	Stage-Coded? (Y/N)	Primary Stage (If Y)	Key DT Characteristics (1–3 Tags)	Notes
[26]	Rahmanzadeh, S (2022)	Journal article	Analytical research—Statistical (analytical)	N		DT applications	
[27]	Iftikhar, A (2024)	Journal article	Analytical research—Statistical (analytical)	N		DT applications	
[32]	Ivanov, D (2021)	Journal article	Analytical research—Mathematical	Y	Preparedness	optimization/planning	
[33]	Singh, G (2023)	Journal article	Empirical research—Case study	Y	Preparedness	DT architecture/deployment	Also related to: Growth
[41]	Rajamurugu, N (2022)	Journal article	Analytical research—Mathematical	N		DT applications	
[42]	Elayan, H (2021)	Journal article	Analytical research—Statistical (analytical)	N		DT applications	
[43]	Ivanov, D (2019)	Journal article	Analytical research—Statistical (analytical)	Y	Preparedness	DT applications	
[44]	Wieland, A. (2013)	Journal article	Analytical research—Mathematical	Y	Growth	DT applications	
[45]	Burgos, D (2021)	Journal article	Analytical research—Mathematical	Y	Growth	simulation/what-if	
[46]	Ivanov, D (2019)	Journal article	Empirical research—Case study	Y	Preparedness	real-time visibility, simulation/what-if, optimization/planning	
[47]	Spieske, A (2021)	Journal article	Analytical research—Mathematical	N		DT applications	
[48]	dos Santos Alvim, S (2022)	Journal article	Empirical research—Case study	Y	Preparedness	DT applications	
[49]	MacCarthy, B (2022)	Journal article	Analytical research—Mathematical	N		DT applications	
[50]	Roman, E (2025)	Journal article	Analytical research—Mathematical	Y	Preparedness	DT applications	Also related to: Rebound
[51]	Zheng, Z (2021)	Conference paper	Analytical research—Mathematical	Y	Preparedness	DT applications	Also related to: Rebound
[52]	Ivanov, D (2023)	Journal article	Conceptual research	Y	Preparedness	simulation/what-if	
[53]	Nguyen, P (2023)	Conference paper	Empirical research—Case study	Y	Resistance	simulation/what-if, DT architecture/deployment	Also related to: Preparedness
[54]	Patidar, A	Journal article	Analytical research—Statistical (analytical)	Y	Resistance	DT architecture/deployment	Also related to: Preparedness, Rebound
[55]	Ivanov, D (2025)	Journal article	Conceptual research	Y	Preparedness	DT applications	Also related to: Rebound

Table 3. *Cont.*

Ref. No.	Author (s), Year	Pub. Type	Research Design	Stage-Coded? (Y/N)	Primary Stage (If Y)	Key DT Characteristics (1–3 Tags)	Notes
[56]	Ashraf, M (2024)	Journal article	Analytical research—Statistical (analytical)	Y	Preparedness	AI/predictive analytics	
[57]	Ashraf, M (2022)	Journal article	Analytical research—Statistical (analytical)	Y	Resistance	AI/predictive analytics, recovery support	
[58]	Zhang, D (2022)	Journal article	Conceptual research	Y	Resistance	DT applications	
[59]	Hanumanthaiah, K (2023)	Conference paper	Empirical research—Case study	Y	Rebound	simulation/what-if, optimization/planning	
[60]	Zhu, X (2025)	Journal article	Analytical research—Mathematical	Y	Rebound	real-time visibility, optimization/planning, DT architecture/deployment	
[61]	Ogunsoto, O (2025)	Journal article	Empirical research—Case study	Y	Rebound	DT architecture/deployment, recovery support	
[62]	Ivanov, D (2023)	Journal article	Conceptual research	Y	Resistance	recovery support	
[63]	Sardesai, S (2023)	Journal article	Analytical research—Statistical (analytical)	Y	Resistance	DT applications	
[64]	Rinaldi, M (2025)	Journal article	Conceptual research	Y	Resistance	traceability & trust	
[65]	Singh, R (2025)	Journal article	Conceptual research	Y	Growth	DT applications	
[66]	Srivastava, G (2025)	Journal article	Empirical research—Case study	Y	Growth	DT applications	
[67]	Guo, D (2025)	Journal article	Conceptual research	N		DT applications	
[68]	Pan, C (2023)	Journal article	Conceptual research	Y	Growth	DT applications	
[69]	Dolgui, A (2025)	Journal article	Empirical research—Case study	Y	Growth	DT applications	
[70]	Marinagi, C (2023)	Journal article	Conceptual research	Y	Growth	DT applications	
[71]	Mylrea, M (2021)	Conference paper	Conceptual research	Y	Growth	AI/predictive analytics, cybersecurity	
[72]	Klöckner, M (2023)	Book/Book chapter	Conceptual research	Y	Growth	DT applications	
[73]	de Farias, I (2022)	Journal article	Empirical research—Statistical (empirical)	Y	Growth	real-time visibility	
[74]	Singh, G (2023)	Journal article	Empirical research—Statistical (empirical)	Y	Preparedness	DT applications	Also related to: Rebound
[75]	Zhang, M (2023)	Journal article	Empirical research—Case study	Y	Resistance	DT applications	Also related to: Rebound
[76]	Singh, D (2024)	Journal article	Empirical research—Statistical (empirical)	Y	Growth	AI/predictive analytics, DT architecture/deployment	

Table 3. *Cont.*

Ref. No.	Author (s), Year	Pub. Type	Research Design	Stage-Coded? (Y/N)	Primary Stage (If Y)	Key DT Characteristics (1–3 Tags)	Notes
[77]	Ivanov, D (2020)	Journal article	Empirical research—Statistical (empirical)	N		simulation/what-if, AI/predictive analytics	
[78]	Kenett, R (2022)	Journal article	Conceptual research	N		DT applications	
[79]	Leung, E (2022)	Journal article	Empirical research—Statistical (empirical)	N		DT architecture/deployment	
[80]	Baruffaldi, G (2019)	Journal article	Conceptual research	N		DT applications	
[81]	Ivanov, D (2022)	Journal article	Empirical research—Statistical (empirical)	N		simulation/what-if, AI/predictive analytics	
[82]	Sundarakani, B (2020)	Journal article	Analytical research—Mathematical	N		optimization/planning	
[83]	Gutierrez-Franco, E (2021)	Journal article	Conceptual research	N		DT applications	
[84]	Lv, Z (2022)	Journal article	Conceptual research	N		DT applications	
[85]	Dąbrowska, A (2021)	Journal article	Empirical research—Case study	N		optimization/planning	
[86]	Abideen, A (2021)	Journal article	Conceptual research	N		DT applications	
[87]	Greis, N (2021)	Conference paper	Empirical research—Statistical (empirical)	N		AI/predictive analytics, DT architecture/deployment	
[88]	Wang, L (2022)	Journal article	Conceptual research	N		DT applications	
[89]	Zdolsek Draksler, T (2023)	Journal article	Empirical research—Case study	N		optimization/planning	
[90]	Dolgui, A (2020)	Journal article	Conceptual research	N		DT applications	
[91]	Kalaboukas, K (2021)	Journal article	Empirical research—Statistical (empirical)	N		DT architecture/deployment	
[92]	Tebaldi, L (2021)	Conference paper	Conceptual research	N		DT applications	
[93]	Badakhshan, E (2022)	Journal article	Conceptual research	N		DT applications	
[94]	Sharma, A (2020)	Journal article	Empirical research—Experimental	N		DT applications	
[95]	Chen, Z (2021)	Journal article	Conceptual research	N		real-time visibility	
[96]	Marmolejo -Saucedo, J (2020)	Journal article	Empirical research—Case study	N		DT applications	
[97]	Nguyen, T (2022)	Journal article	Conceptual research	N		DT applications	
[98]	Simchenko NA; Tsohla SY;(2020)	Journal article	Conceptual research	N		DT applications	
[99]	Resman, M (2021)	Journal article	Analytical research—Mathematical	N		optimization/planning, DT architecture/deployment	

Table 3. *Cont.*

Ref. No.	Author (s), Year	Pub. Type	Research Design	Stage-Coded? (Y/N)	Primary Stage (If Y)	Key DT Characteristics (1–3 Tags)	Notes
[40]	Kamble, S (2022)	Journal article	Empirical research—Statistical (empirical)	N		DT architecture/deployment	
[100]	Frankó, A (2020)	Journal article	Conceptual research	N		real-time visibility	
[101]	Kajba, M (2023)	Journal article	Empirical research—Statistical (empirical)	N		DT applications	
[102]	Lugaresi, G. (2021)	Journal article	Empirical research—Case study	N		optimization/planning	
[103]	Golan, M (2021)	Journal article	Empirical research—Statistical (empirical)	N		DT architecture/deployment	
[104]	Dy, K (2022)	Conference paper	Empirical research—Case study	N		DT architecture/deployment	
[105]	Park, K.T (2021)	Journal article	Empirical research—Case study	N		DT deployment	

4. Research Findings

In this section, we discuss the main themes emerging from the reviewed sample of articles. In doing so, we provide answers to the three main research questions that this study put forward.

4.1. Descriptive Analysis

The aim of the descriptive analysis is to quantitively summarise the publication trend by date, main subject areas addressed, theoretical approaches, methodologies employed, and publication journals, providing an overview of the development of knowledge in the subject area under investigation.

4.1.1. Publication Trend

Figure 5 shows the annual distribution of studies examining digital twin applications for supply chain resilience. The first article in this stream appeared in 2013, and publication activity remained sporadic until 2018, with only a small number of studies published during this early period. From 2019, however, the field expanded rapidly: output rose from three studies in 2019 to 13 in 2020, 19 in 2021, and 18 in 2022. Publication volume remained high in 2023 (seventeen studies), followed by five studies in 2024. In 2025, eight studies were identified in the current dataset.

Overall, this pattern suggests that digital twin-enabled supply-chain resilience is an emerging but fast-developing research area, with the strongest growth concentrated between 2019 and 2023. While the foundational idea of the digital twin can be traced back to early engineering applications such as NASA's Apollo-era practices in the 1970s [106], explicit scholarship linking digital twins to supply-chain resilience has only gained sustained momentum in the last decade, accelerating markedly after 2019. The growth in publications is likely linked to the wider recognition of the potential of digital twins for risk management and continuity planning in supply chains, with the accelerated shift towards digital and data-driven supply chains after COVID-19 playing an important role.

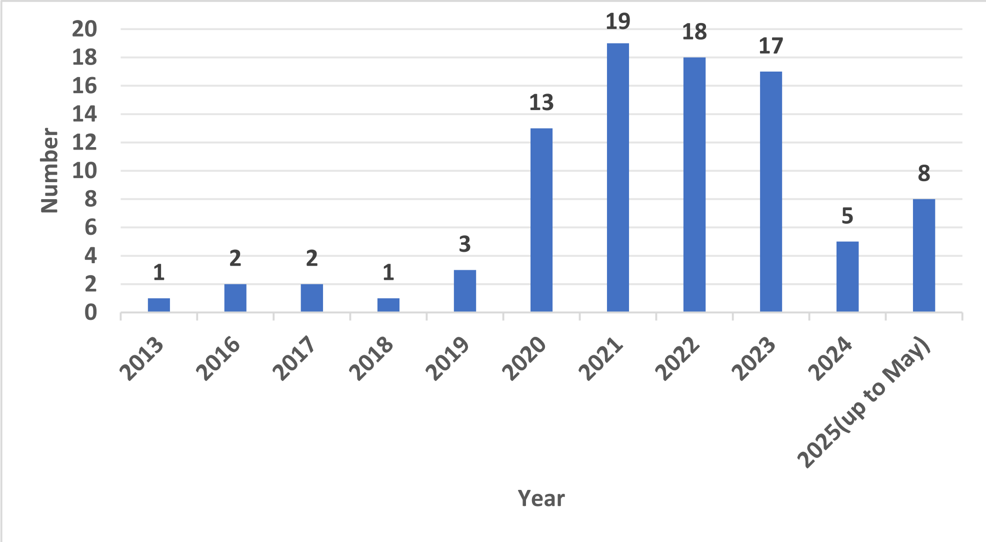

Figure 5. Publication trend. Evolution of publications.

4.1.2. Research Areas Distribution

Figure 6 summarises the industrial sector distribution of studies exploring the adoption of digital twins for enhanced supply-chain resilience (out of the 89 selected articles, only 22 specify a sector of application). The largest group of publications focuses on pharmaceutical supply chains, with seven studies, followed by food supply chains with five studies, and manufacturing with four studies. Automotive and multi-sector studies each account for two publications, while electricals and financial services are represented by one study each. This distribution shows that research on digital twins in supply-chain resilience is concentrated in a few critical industries rather than being evenly spread across all sectors.

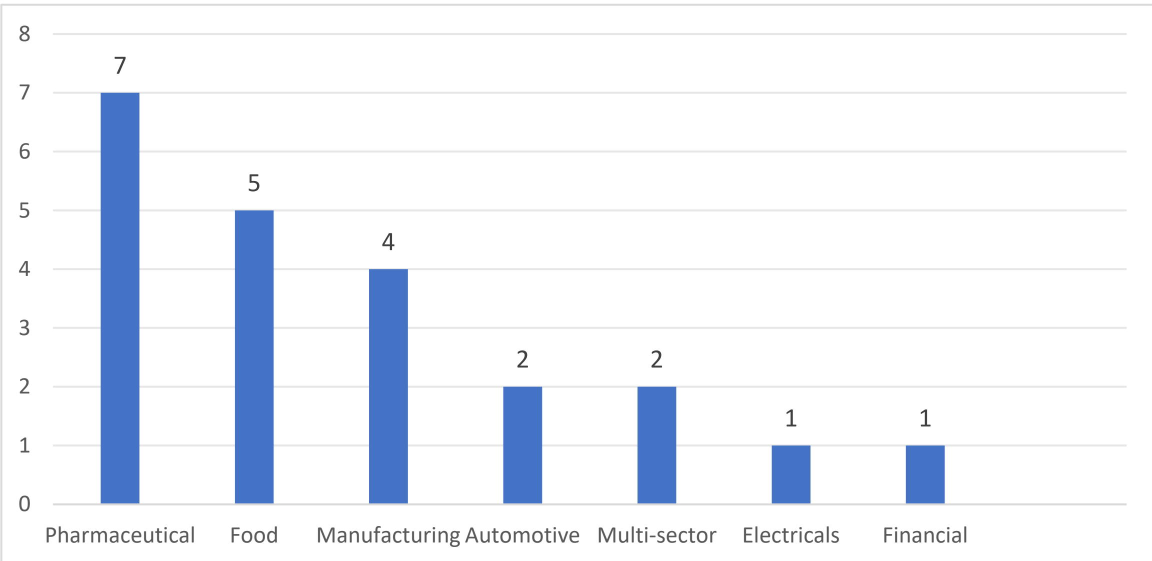

Figure 6. Research areas distributions.

The prominence of pharmaceutical and food supply chains can be linked to the high vulnerability of these sectors to disruption and to their strict quality and safety requirements. Firms in these sectors face strong pressure to ensure continuity of supply, maintain product integrity, and comply with regulations, which creates a strong motivation to explore digital twins as tools for visibility, risk analysis, and contingency planning. Manufacturing supply chains also appear frequently, reflecting the role of digital twins in supporting Industry

4.0, real-time monitoring and disruption management on the shop floor. By contrast, automotive, multi-sector, electrical, and financial applications are still relatively scarce, which suggests that the potential of digital twins for resilience in these sectors remains underexplored and offers opportunities for further research

4.1.3. Distribution of Journals

The selected 89 articles appeared in 34 separate journals, highlighting the multidisciplinary nature of DTT. To avoid a long tail on the graph, Figure 7 only shows those journals that published more than one article. In addition, work examining the interface between digital twins and supply chains is represented in outlets such as IFAC-PapersOnLine (four articles) and Logistics (three articles).

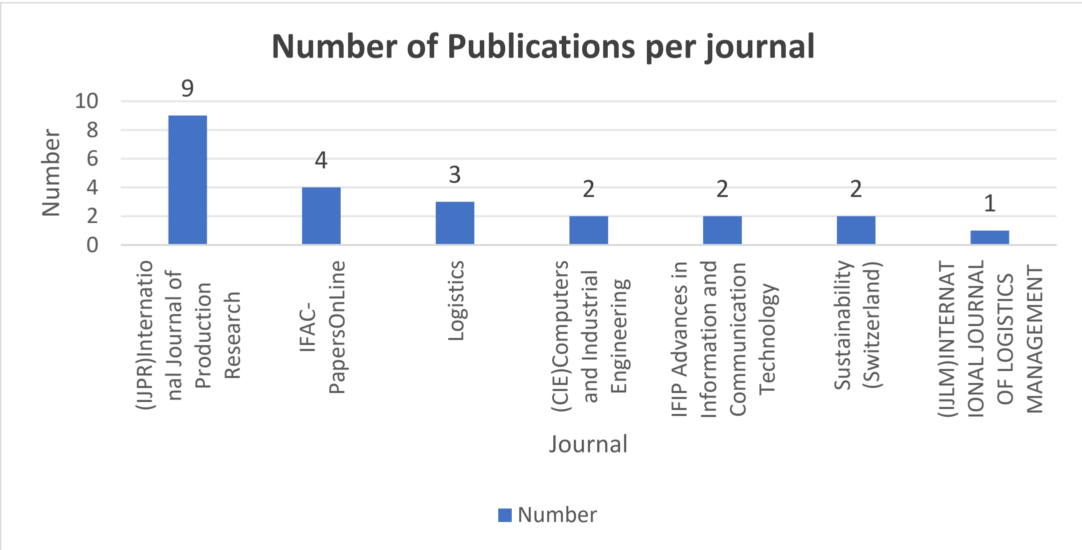

Figure 7. Publication distribution across journals.

4.1.4. Research Methods and Data Analysis Techniques

To categorise the selected articles by research design, this study draws on [107]'s distinction between theory-building and empirical research, which has been applied in operations management reviews to identify patterns in published work [45,108]. For clarity, theory-building studies are further separated into conceptual research and analytical modelling research. Conceptual studies develop definitions, frameworks, taxonomies, and propositions, whereas analytical modelling studies use formal methods such as mathematical modelling, optimisation, simulation or statistical modelling to derive implications that can later be empirically tested.

Empirical research, by contrast, uses data from external organisations to test whether emerging concepts and proposed relationships are held in the real world. Wacker distinguishes three subcategories here as well, namely, experimental research, empirical statistical research, and case study research. Experimental and empirical statistical studies test hypothesised relationships on larger samples, whereas case studies investigate a smaller number of organisations in depth and often use qualitative data

Table 4 summarises the distribution of methods across the 89 selected articles. Overall, theory-building research dominates the knowledge base on digital twins and supply-chain resilience. Conceptual research represents the largest single category, with 24 publications developing definitions, frameworks, or taxonomies relevant to digital-twin-enabled resilience. Analytical modelling studies account for a further 29 articles, comprising 18 analytical statistical studies, and 11 analytical mathematical studies that use approaches such as formal modelling, optimisation, and simulation. Empirical research accounts for 36 articles. Within the empirical category, case study research is the most common approach, with 21 articles examining digital twin applications in specific supply-chain settings. Empirical statistical studies, often based on surveys or archival datasetsand analysed using methods such as regression or partial least squares structural equation modelling, account for 14 articles. Only one study adopts an experimental design.

Table 4. Summary of the publications based on their methodological approach.

Type of Research	Subcategory	Number of Papers
Conceptual research	Conceptual research	24
Analytical research	Mathematical research	11
	Statistical research (analytical)	18
Empirical research	Experimental research	1
	Statistical research (empirical)	14
	Case study	21
Total		89

The distribution across subcategories indicates that the knowledge base on digital twins for supply-chain resilience is expanding and developing beyond the pure conceptual. Conceptual research, empirical case studies, and empirical statistical work together account for the majority of publications, which means that scholars both generate new theoretical insights and increasingly test these ideas in real settings. This balance between theory building and empirical examination is often seen as a characteristic of a maturing research field [23]. Analytical mathematical studies, although fewer in number, still form an important strand, as they provide detailed models of disruption propagation, recovery policies, and network reconfiguration using approaches such as discrete event simulation and optimisation for example [32,46]. At the same time, the relatively small share of experimental and empirical statistical studies suggests that rigorous large-scale testing of digital-twin-based resilience mechanisms remains limited.

Overall, the pattern reported in Table 4 points to a field that is still driven mainly by conceptual reasoning and model-based analysis, but where empirical applications are beginning to catch up. Conceptual contributions continue to refine definitions of supply-chain resilience, identify relevant drivers, and map how digital twins interact with other technologies such as artificial intelligence or blockchain. Case studies demonstrate how these ideas play out in practice, for instance by using digital twins to support predictive maintenance, improve end to end visibility, or evaluate contingency plans in specific supply chains. Empirical statistical work provides initial quantitative evidence on the effects of digital twin adoption on visibility, agility, and resilience. However, the limited number of experimental and large sample statistical studies shows that more applied research is needed before the field can be considered fully mature, and that further empirical validation of digital twin applications in supply-chain resilience remains an important avenue for future work.

4.2. Content Analysis—Digital Twin Applications in Supply-Chain Resilience

In this section, we synthesise how digital twin capabilities may enhance supply-chain resilience across four stages, preparedness, resistance, rebound, and growth. Full texts were coded manually in NVivo and Microsoft Excel using an abductive approach that moved iteratively between data and theory, combining inductive identification of emerging concepts with deductive use of established resilience constructs. The stage logic is grounded in the three-stage resilience process proposed in [23], preparedness, resistance, and rebound, and is extended with a fourth growth stage based on [24]. In [24], growth captures resilience that exceeds recovery by not only returning to a normal state after a risk event but achieving a new and improved position. Drawing on the subset of studies that explicitly connect digital twins, or closely related digital representations, to resilience constructs in supply-chain and operations contexts (Table 5; Figure 8), we identify stage-associated capability patterns. Preparedness is most often linked to end-to-end visibility, predictive risk analytics, virtual stress testing, and resilient network design. Resistance is most often linked to real-time disruption detection, adaptive control, data-driven coordination, and predictive maintenance. Rebound is most often linked to predictive recovery modelling, recovery path evaluation, resource reconfiguration support, and workflow automation. Growth is most often linked to post disruption analysis, capability development, and strategic redesign.

Table 5. Digital twin in four stages of supply-chain resilience.

Supply-Chain Resilience Stage	Related References (Author and Year)	Number of Articles
Preparedness	[14,32,33,43,46,48,50–56,74]	14
Resistance	[53,54,57,58,62–64,75]	7
Rebound	[50,51,54,55,59,61,74,75]	8
Growth	[33,44,65,66,68–73,76]	11

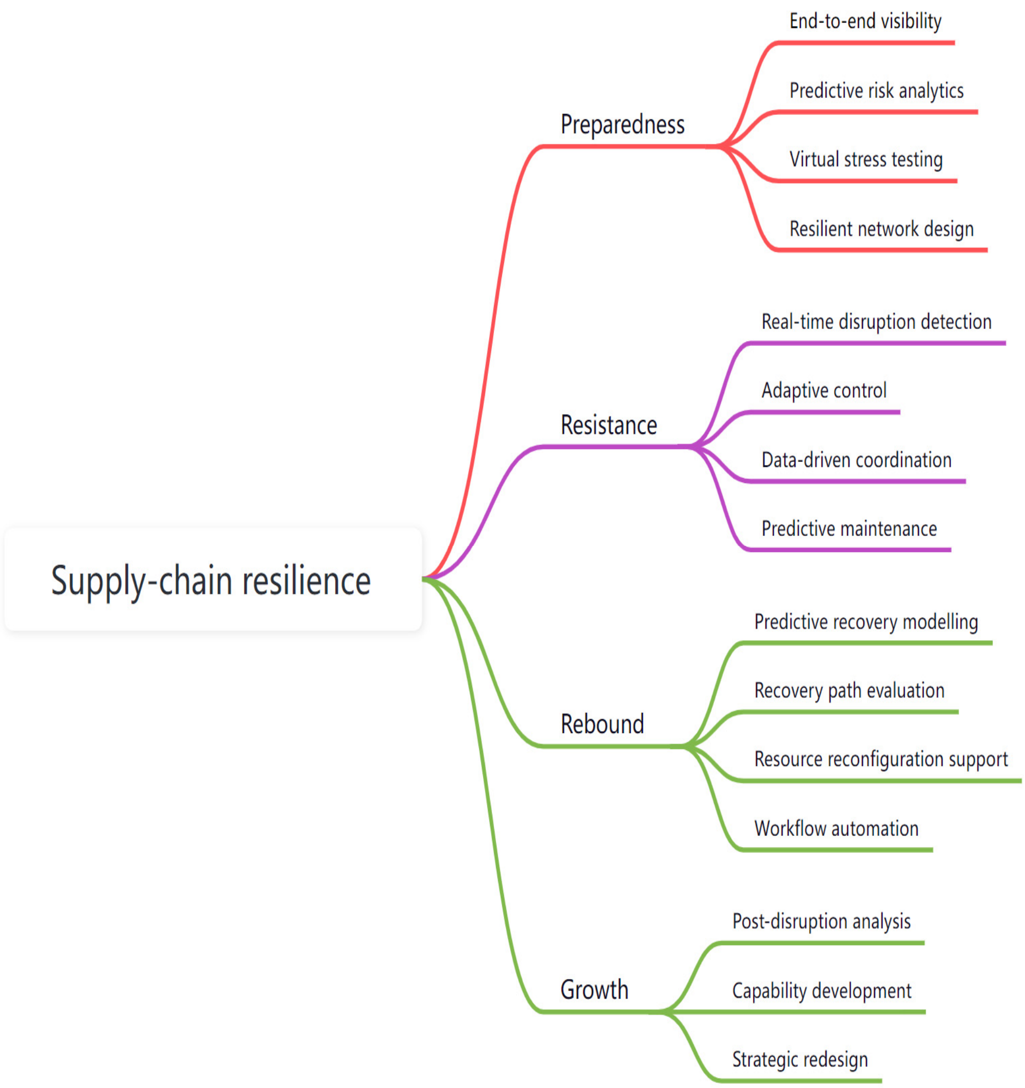

Figure 8. Extended four-stage framework of digital twin capabilities for supply-chain resilience adapted from [23].

The four-stage framework was selected because resilience is inherently temporal and stage dependent, and because digital twins tend to be mobilised differently before, during, and after disruptions. Building on [23] and the growth extension in [24], the framework is used as an organising lens rather than a claim that all digital twin applications follow discrete or linear stages. Stage boundaries may overlap, and some capabilities can plausibly support multiple stages. Where this occurred, we assigned the capability to the stage most explicitly described and evidenced in the source text, while noting cross-stage relevance in the narrative synthesis.

Two levels of coding were applied. First, all 89 included articles were coded for digital-twin-related benefits and challenges in supply-chain contexts affected by risk, disruption, or uncertainty. These codes underpin the synthesis in the Benefits and Challenges sections and the summaries in Tables 6 and 7. Second, a narrower subset of 40 articles that explicitly linked digital twins, or closely related digital representations, to resilience constructs and provided sufficient temporal and mechanistic detail for stage assignment was coded against the four-stage framework (Table 5). The remaining 49 articles informed the wider benefits and challenges synthesis but did not contain enough stage-specific information to be classified confidently into individual resilience phases. These articles did not conflict with the framework. Instead, most discussed general digital twin benefits, enabling technologies, or adoption considerations without specifying disruption timing or stage relevant mechanisms. To reduce the risk of selection bias, they were retained in the broader synthesis and screened for recurring capability themes. Where capability themes were present but could not be tied to a specific stage, they were treated as cross cutting and discussed outside the stage mapping rather than being forced into a stage classification.

Table 6. Digital twin application benefit.

Digital Twin Application Benefits	Related References (Author and Year)	Number of Articles
Real-time monitoring	[6,19,40,45,78,79,84,88,89,93,100–104]	15
Improve decision-making	[7,13,15,27,30,47,48,51,52,74,75,77,79,82–84,88,90,91,101,108]	21
Predictive maintenance	[77,82–84,86,87,102]	8
Risk reduction	[9,15,17,18,33,75,79,86,87,89,90,92,108,109]	15
Time and cost saving	[46,48,50,55,57,62,80,91–93]	10
Improved efficiency	[1,7,8,14,16,45,53,76,77,84,85,94,96,97,109]	15
Supply-chain collaboration	[7,47,57,77,86,94,95,108]	8

Table 7. Digital twin application challenges factors.

Digital Twin Application Challenges	Related References (Author and Year)	Number of Articles
Data interoperability	[6,8,17,93,96]	5
Data accuracy and reliability	[7,11,27,87]	4
Cost	[10,27,30]	3
Data security and privacy	[8,20,57,86,93]	5
Model complexity	[27,32,36]	3
Connectivity	[50,94]	2
System compatibility	[2,7,94,96]	4

In this review, a digital twin capability is defined as a DT-enabled functional mechanism that can be mobilised to support resilience, such as end-to-end visibility, predictive risk analytics, or workflow automation. Capabilities are conceptually distinct from benefits and outcomes, such as improved service levels or reduced costs, and from adoption barriers, such as data quality limitations or interoperability constraints. Stage assignment followed explicit decision rules aligned with the temporal logic of resilience. Preparedness refers to ex ante sensing, planning, design, and stress testing before disruption. Resistance refers to in event detection, absorption, and control to maintain acceptable performance during disruption. Rebound refers to post event recovery decisions, reconfiguration, and restoration of performance. Growth refers to post recovery learning, capability development, and strategic redesign that enables improvement beyond restoration [23,24]. Only studies providing sufficient stage explicit detail were classified into the four-stage capability map (Table 5; Figure 8), while studies lacking stage explicit mechanisms contributed to the broader benefits and barriers synthesis (Tables 6 and 7).

4.2.1. Preparedness Stage

Preparedness refers to the ability of the supply chain to anticipate disruptions and to design appropriate structures and plans before an event occurs. The reviewed studies suggest that digital twins may support preparedness through four capabilities: end to end visibility, predictive risk analytics, virtual stress testing, and resilient network design.

Several conceptual and literature review articles treat digital twins as a central visibility layer that makes supply-chain structures and flows observable at a fine level of granularity. Ivanov describes a digital supply-chain twin as a model that continuously represents the network state and enables full end-to-end visibility for disruption risk management and contingency planning [32,47]. Similar arguments appear in work on visibility models and Industry 4.0 frameworks, where digital twins, the Internet of Things and blockchain are combined to build pharmaceutical supply-chain visibility and to quantify the effects of flexibility and agility on resilience [48,49]. Bibliometric and systematic reviews also identify "supply-chain resilience and risk management" as a distinct value cluster within the digital twin research stream, which suggests that visibility through digital replicas is becoming an established preparedness capability rather than a speculative idea [14,50,51].

Digital twins further enhance preparedness through predictive insight. Data-driven technologies such as big data analytics and machine learning are frequently embedded in supply-chain twins to forecast disruption likelihood, demand surges, or capacity bottlenecks. For instance, a PLS SEM study on manufacturing supply chains finds that digitalisation, including twin adoption, improves sustainability indirectly by strengthening supply-chain resilience and performance, and the authors explicitly link this effect to better anticipation of disruptions and more robust planning decisions [44]. A conceptual chapter on data-driven technologies during COVID 19 explains how digital twins, big data, and blockchain create a real-time picture of material positions and vulnerabilities, which allows managers to recognise weak points in global networks and to plan emergency capacities and alternative sourcing paths in advance [52]. The intelligent digital twin concept proposed by Ivanov positions digital twins as human AI systems that continuously monitor early warning indicators, run predictive analytics, and translate signals into recommendations for stress testing and proactive protection measures [53].

Preparedness also benefits from the ability of digital twins to support virtual stress testing and network design before disruptions occur. Simulation based studies use anyLogistix or other discrete event tools to instantiate digital twins of food retail or semiconductor supply chains, explore pandemic or shortage scenarios and identify critical parameter combinations well before similar conditions materialise in reality [46,54]. A weighted Ishikawa diagram study on developing economies systematically ranks traditional resilience factors, such as redundancy and robustness, and proposes the development of digital twins and blockchain as future research directions for quantifying how alternative network designs would behave under disruption [55]. Reconfigurable supply-chain concepts similarly argue that reconfigurability should be designed into the network ex ante and that digital technologies such as digital twins will be essential to explore "dynamic meta structures" and autonomous service configurations in silico before implementation [56].

Taken together, these studies suggest that digital twins extend the [24] preparedness stage by adding predictive and experimental capabilities to the classical focus on structural redundancy and visibility. Preparedness no longer only means holding buffer inventory or multiple suppliers; it also means maintaining a living digital representation that continually tests "what if" scenarios and informs design choices before a disruption strikes.

4.2.2. Resistance Stage

Resistance describes the ability of a supply chain to absorb the initial impact of disruption and to maintain an acceptable level of performance while the event unfolds. Digital twins contribute to this stage by enabling real-time sensing, adaptive control, and data-driven coordination across the network.

Analytical and case study work shows that digital twins can improve the adaptability of inventory, production, and logistics processes during crises. In food retail supply chains, a digital twin built with discrete event simulation is used to represent German supermarket operations under different COVID-19 lockdown intensities; the analysis shows that the twin can be used to explore combinations of ordering policies, demand surges and supplier shutdowns that keep service levels within acceptable ranges while controlling transport costs, thereby strengthening resistance during the pandemic [46]. A semiconductor shortage study combines case evidence from Intel concludes that manufacturing flexibility, velocity, and contingency plans represent key resistance measures that can be evaluated and coordinated through a digital supply-chain twin [54].

Digital twins also support resistance by providing disruption detection and dynamic control in near real time. Several mathematical and experimental articles develop cognitive or intelligent supply-chain twins that integrate deep learning for disruption detection, anomaly recognition and time to recover prediction. A hybrid deep learning approach uses an autoencoder and one class support vector machine to detect disruptions in a digital supply-chain twin, while long short-term memory models identify the disrupted echelon and predict recovery time; the authors show that this cognitive twin enables decision makers to trigger response actions more quickly and to balance sensitivity against false alarms [57]. Another study combines discrete event simulation with a long-short term memory (LSTM) model to predict time to recover within a three-echelon supply chain, thereby providing early estimates of how long a disruption will affect service levels [58]. Vulnerability evaluation of a smartphone assembly workshop embeds queuing models and reliability analysis inside a digital twin to calculate temporal and spatial vulnerability indicators, which can guide buffer allocation and control decisions during disturbances [59].

Resistance is not only about sensing; it also requires adaptive execution of mitigation strategies. Work on digital twin enhancement shop floors shows that an integrated twin can support real-time disruption management through end-to-end visibility, process streamlining, and decision support at the manufacturing level, which in turn stabilises the supply chain during supply and demand shocks [42]. Master planning studies use hybrid modelling frameworks that combine simulation, machine learning and optimisation to update production, storage, and distribution decisions when demand or lead times change unexpectedly; the results show that such digital twin precursors increase service levels and contain costs in the presence of disruptions. Simulation-based optimisation experiments that layer digital twins on top of enterprise resource planning systems further indicate that dynamic "what if" analyses can support more intelligent responses to disruptions than static planning tools, even though many of these contributions still focus on method development rather than full-scale twin implementations [60,61].

Overall, the literature suggests that digital twins enrich the resistance stage by transforming static contingency plans into a set of data-driven control capabilities. The supply chain can sense and localise disturbances through the DT, simulate alternative operational responses and implement more flexible production, inventory and transport strategies in near real time.

4.2.3. Rebound Stage

Rebound relates to the ability of the supply chain to return to its target performance level after a disruption and to restore the viability of the network. The reviewed studies show that digital twins support rebound by predicting recovery trajectories, evaluating sustainable recovery options and institutionalising learning from simulated crises.

A conceptual digital twin framework for recovery and resilience proposes a three-phase architecture that illustrates this role very clearly. In the first phase, machine-learning models predict the occurrence of floods; in the second phase, discrete event simulation replicates the breakdown of value chains; in the third phase, a neural network uses simulated data to predict recovery indicators such as service restoration time [62]. The authors argue that such a twin allows planners to understand how different combinations of protective measures, network designs and recovery resources affect the time to recovery, which directly operationalises the rebound stage. Time to recover prediction within digital twin environments, as already noted in the LSTM-based work on three echelon supply chains, also represents a concrete measure of rebound capacity rather than a purely qualitative concept [57,58].

Recovery strategies that combine resilience and sustainability can also be assessed in digital twin environments. Design and deployment of sustainable recovery strategies for a manufacturing supply chain uses anyLogistix digital models to compare ad hoc air freight-based reactions with alternative recovery strategies that employ additive manufacturing and electric trucks; the study finds that the proposed strategies reduce both emissions and disruption-related losses compared with conventional reactions, which indicates that digital twins can help identify recovery paths that support both resilience and environmental objectives [53,63]. A process capability index-based resilience analysis shows how a digital twin of an automotive supply chain can be used to evaluate different reconfiguration options against a composite resilience index, thereby supporting the rapid selection of recovery paths that balance performance and cost [64].

Several conceptual contributions broaden the rebound discussion by emphasising the role of digital twins in learning from disruptions. The intelligent digital twin framework argues that stress testing and disruption simulation should not end when the crisis is over but should feed back into the model as new decision rules and knowledge about effective policies [53]. Semiconductor and vaccine case studies report that lessons from digital-twin-based analyses during crises can inform structural changes such as shifting inventory upstream or redesigning sourcing strategies, which improve readiness for future events [54,65]. These insights suggest that rebound in a digital twin context is not a simple return to the pre disruption state; rather, it is a recovery to an adjusted configuration that incorporates learning from simulated and realised disruptions.

4.2.4. Growth Stage

The growth stage captures the extent to which supply chains use disruptions and the associated digital investments as a basis for long term capability development and strategic renewal. This stage extends [24]'s original framework and aligns with the four-stage resilience perspectives that add a growth or adaptation phase after recovery. The literature on digital twins and resilience contains a growing number of contributions that speak directly to this stage.

Survey-based studies demonstrate that digital twin adoption is associated with broader strategic benefits that go beyond short-term crisis management. Empirical work on manufacturing supply chains using partial least squares structural equation modelling finds that digital twins improve supply-chain sustainability indirectly through supply-chain resilience and performance, and the authors discuss how these relationships reflect the development of dynamic capabilities for coordination, visibility, and analytics rather than one-off projects [44]. Similar PLS SEM studies in humanitarian contexts reveal that intangible resources such as innovation culture, collaborative networks, and stakeholder engagement significantly enhance the effect of digital twin integration on resilience and agility, which points to a long term co evolution of technological and relational capabilities [66,105]. A framework for machine learning and digital-twin-enabled resilience in the Indian fast moving consumer goods sector uses interview data to identify visibility, analytics, inventory management and understanding of consumer behaviour as enduring capabilities that help firms continuously adjust to changing environments and grow [67].

Conceptual literature further positions digital twins as part of broader digital transformation and sustainability agendas. Work on lean supply-chain management argues that digital twins not only support traditional lean pillars but also contribute to integration, coordination, collaboration and flexibility, which collectively enhance resilience and adaptability at the system level [68]. Knowledge mapping of resilience and human rights in supply chains introduces a roadmapping taxonomy for a twin green and digital transition and highlights digital technologies, including digital twins, as key instruments for enhancing human-centred resilience and sustainability practices over time [69]. The Internet of Behaviours framework extends this argument by showing how behavioural analytics combined with digital supply-chain twins can support anomaly detection in supplier and customer behaviour, opening avenues for new product introductions and more resilient demand and supply planning [70]. Studies on Industry 4.0 technologies and key performance indicators for resilient supply chain 4.0 identify digital twins as one of several technologies that improve flexibility, collaboration and visibility metrics, thereby embedding resilience within performance management systems rather than treating it as a separate domain [71].

Several case-based chapters also illustrate how digital twins catalyse new organisational forms and governance structures as part of a growth strategy. The BioSecure digital twin initiative in biopharmaceutical manufacturing presents a national-level platform that combines cyber security, monitoring, and control to protect critical production systems and supply chains from cyber threats; the initiative is explicitly framed as a long term transformation of national resilience rather than a project tied to a specific disruption [72]. Emergency supply-chain resilience work that integrates blockchain with simulation-based modelling argues that digital technologies build institutional memory and improve coordination mechanisms for future vaccine campaigns and other crises [65]. Chapters on building resilient post-pandemic supply chains emphasise that digital twins, together with other technologies such as analytics and platforms, can support strategic choices regarding collaboration, flexibility, and redundancy that position firms better for future turbulence [73].

In summary, the growth stage in a digital-twin-enabled resilience framework reflects the shift from isolated resilience projects to an embedded digital capability that continually supports innovation, sustainability, and strategic redesign. Digital twins help organisations to internalise lessons from disruptions, to institutionalise new data-driven routines and to align resilience objectives with broader performance and sustainability goals.

Across all four stages, the reviewed literature suggests that digital twins act as an integrating technology that connects data, models, and decision processes in supply chains. Preparedness benefits from predictive visibility and stress testing, resistance benefits from real-time disruption detection and adaptive control, rebound benefits from recovery prediction and evaluation of alternative recovery paths, and growth benefits from the accumulation of digital capabilities and organisational learning. At the same time, the empirical base is still relatively small and often concentrated in specific sectors such as food retail, semiconductors, and humanitarian logistics, which indicates substantial opportunities for further applied and longitudinal research on digital twins and supply-chain resilience.

4.3. Additional Digital Twin Application Benefits

In this section, we delve into the multifaceted benefits of digital twin applications across various industries. Our literature review was able to identify that, while DTT adoption enhances SC resilience, it also offers a wider array of advantages, including real-time monitoring, decision-making improvement, more effective predictive maintenance, risk reduction, time and cost savings. Additionally, digital twins improve overall operational efficiency and enable seamless collaboration within complex global supply-chain networks. These additional benefits are discussed in detail in the following sections and are summarised in Table 6.

4.3.1. Real-Time Monitoring

Through the utilisation of virtual replicas of actual systems or objects, DTT makes it possible to accurately and continuously monitor processes in the real world [56,77]. Instantaneous insights into the state, functionality, and circumstances of the physical system can be obtained through real-time capture via sensors and Internet of Things (IoT) devices [78,79]. This capability facilitates early detection of possible problems, enabling prompt action and proactive decision-making. All things considered, the advantages include increased operational effectiveness, better maintenance procedures, and the capacity to react quickly to situations that change. Ultimately, real-time monitoring leads to better system visibility, which can then lead to a lot of the further benefits highlighted below.

4.3.2. Decision-Making Improvement

The enhanced system visibility that DTT enables can be used for more accurate predictive analytics, enhanced risk management capabilities and better decision-making abilities. Decision-makers can utilise historical data analysis as well as real-time data to simulate scenarios in order to forecast future events, allocate resources more optimally, and anticipate problems before they arise [77,80–84] Proactive decision-making leads to cost optimisation as well as improved operational efficiency and resilience. Moreover, DT could enhance the efficient monitoring and management of resources, promote effective stakeholder engagement, and permit adaptive decision-making in response to changing circumstances. Essentially, digital twins provide decision-makers with an extensive toolkit to help them make well-informed, resource-efficient, and forward-looking judgements.

4.3.3. Predictive Maintenance

DTT can provide substantial benefits for advanced predictive maintenance within various industries. By creating a virtual replica of physical assets and continuously collecting real-time data through sensors and IoT devices, the digital twin enables the prediction of potential issues and the scheduling of maintenance activities before equipment failure occurs [82–84]. Predictive maintenance is aided using DTT for real-time monitoring as it may identify abnormalities or departures from typical behaviour, averting equipment breakdowns and cutting downtime [77,86,87,102]. This proactive strategy lowers total maintenance costs, increases asset longevity and minimise downtime. Utilising machine learning algorithms to evaluate both past and present data, predictive maintenance with digital twins finds patterns and trends that point to imminent problems. In addition to increasing equipment dependability, this also helps with safety, operational effectiveness, and resource optimisation.

4.3.4. Risk Reduction

DTT plays a crucial role in risk reduction across diverse industries. By creating a virtual representation of physical system or processes, the digital twin would establish the dynamic platform for modelling and analysis of potential bottlenecks. Organisations can use these simulation capabilities to evaluate the effects of different scenarios, spot weaknesses, and take preventative action to reduce risks [9,90–92]. As such, Digital Twins provide early identification of abnormalities or deviations from normal operations by real-time monitoring and analysis of data from sensors and IoT devices, allowing quick reaction to possible threats [90]. In addition to improving operational safety, this risk reduction approach safeguards resources, reduces downtime, and strengthens overall business resilience.

4.3.5. Time and Cost Savings

DTT offers significant advantages in terms of cost and time savings across various process. Organisations can simulate and optimise activities prior to executing them in the real world by building a virtual duplicate of physical systems [80,91,92]. It is possible to identify inefficiencies, bottlenecks, and possible cost-saving strategies thanks to this simulation capacity. By improving process visibility and cutting down on the time needed for problem identification and resolution, real-time monitoring using sensors and Internet of Things devices is possible. All things considered, digital twins improve productivity, simplify processes, and save a significant amount of money and effort for businesses.

4.3.6. Supply-Chain Collaboration

With the ability to view the whole supply chain from a shared, real-time perspective, DTT greatly enhances supply-chain cooperation [93,94]. Digital twins facilitate smooth information sharing between stakeholders by creating virtual copies of real assets and processes. With precise and current data at hand, collaborative decision-making is made possible by this shared visibility. Digital twins integrated with predictive analytics offer early warning signs of possible problems, encouraging proactive problem-solving. By working together, stakeholders can evaluate and reduce risks, improving the resilience of the supply chain. Centralised platforms also allow efficient communication, minimising miscommunication and delays. Process optimisation turns into a team effort where participants modify distribution, inventory, and manufacturing in response to actual demand [21,98]. The shared data can facilitate accountability and continual improvements [93,96]. Digital twins can thus be a uniting tool that promotes cooperation across complex global supply chains [75,76,82].

4.4. Digital Twin Application Challenges

The application of DTT in supply-chain resilience presents several challenges that require careful consideration. These challenges encompass various aspects shown in Table 7, which include data security, accuracy, and complexity, as well as practical concerns such as installation cost and system compatibility. Among these challenges, data security and privacy, along with data collection, are particularly prominent, as DTT heavily relies on data-driven processes.

4.4.1. Data Interoperability

DTT is a technology that highly relies on data transmission and connection; therefore, ensuring data sharing and system interoperability is very important. Due to the need for data collection from various resources, platforms, and systems, usually spread out along complex supply chains, integrating multiple data types can be complex and time-consuming. Ref. [93] found that information asymmetries and data interoperability are usually the main challenges in supply-chain management when adopting DTT. Each stakeholder may utilise different data structures and software systems, making it challenging to harmonise and combine data seamlessly. Multiple types of data forms can lead to data incompatibility, duplication, and quality issues.

4.4.2. Data Accuracy and Reliability

The real-time transmission of data and end-to-end network connectivity are essential components for building a robust digital twin simulation model. Environmental factors like rainstorms, snowstorms, and physical obstacles can also disrupt the data transmission process, affecting the reliability of the digital twin model [7]. Additionally, the collection of large volumes of data necessitates the deployment of numerous sensors, which may incur substantial costs for companies. As a result, a thorough assessment of the communication infrastructure's adequacy for successful data collection becomes imperative before embarking on digital twin initiatives [11,87]. Furthermore, even when sufficient data is available, organising and analyzing it to extract meaningful insights remains a significant challenge.

4.4.3. Cost

The adoption of DTT in SCR can be costly. Ref. [27] highlight the significant investment required in IT infrastructure to establish a DTT software platform. This infrastructure encompasses data collection systems, sensors, relevant Internet of Things (IoT) devices, and corresponding IT services for software upgrades and data storage. Another cost consideration concerns the integration of DTT with augmented reality (AR) or cloud computing. As ref. [30] point out, capturing real-time data with high accuracy necessitates cloud computing and AR technology. The installation and implementation of these technologies add another layer of significant cost.

4.4.4. Data Security and Privacy

Data security and privacy pose another significant challenge in supply-chain management [20]. The inherent interconnectedness of the supply-chain process necessitates numerous data exchanges between various stakeholders. A data breach or unauthorised access to this sensitive information can incur substantial financial losses, reputational damage, and legal repercussions, potentially leading to unintended conflicts across the supply chain. Furthermore, the reliance on cyber networks for data transmission exposes vulnerabilities to cyberattacks. These attacks can lead to data leakage, unauthorised modification, or disruption. Malicious actors may specifically target digital twin platforms to disrupt supply-chain operations, steal sensitive information, and compromise the integrity of the digital twin model [93].

4.4.5. Model Complexity

Since supply chains are intrinsically complicated and digital twins are intended to generate virtual representations of real-world systems, it can be difficult to construct accurate and effective digital twin models [27,101]. Supply chains are multi-component, multi-node, multi-process systems that are dynamic and interrelated. Complex modelling strategies are needed to capture and portray the relationships and interactions between different digital twin model components [32]. A typical supply-chain process encompasses procurement, manufacturing, transportation, and warehousing activities. Integrating data and processes from these disparate domains into a unified digital twin model can be a complex and time-intensive undertaking.

4.4.6. Connectivity

DTT connectivity presents challenges across two key aspects: data transmission latency and dynamic processing synchronisation [50]. For decision-making support and timely insights, real-time data transfer is crucial. However, network congestion, bandwidth restrictions, or physical distance between data sources and the digital twin platform might cause data transmission lag. Supply-chain operations are fluid and complex and transferring data into the system in a timely manner while reflecting changes in supply-chain dynamics in real time presents significant challenges.

4.4.7. System Compatibility

Another major obstacle to the use of DTTs in supply chain is system compatibility. Within the supply-chain ecosystem, DTTs frequently interact with a variety of pre-existing systems, programs, and hardware elements. It might be difficult to ensure flawless compatibility between these many components [96]. Supply chains frequently include a variety of systems and technologies from many providers. These systems could employ several operating systems, communication protocols, and data formats, making it difficult to smoothly connect them with the DTT platform. Many supply-chain companies still rely on antiquated software that cannot be easily integrated with contemporary DTT. It might take a lot of resources to retrofit these old systems to work with the digital twin platform.

5. Discussion

This study employed a systematic literature review methodology to synthesise and identify research trends in DTT applications in supply-chain resilience. While our article highlights that applications of digital twins in supply-chain resilience remain in their infancy, the systematic analysis adopted consolidates various academic perspectives and practical developments in the industry and summarises the current stage of knowledge on the topic. The main findings of our study are summarised below, as answers to the research questions originally put forward.

5.1. Answers RQ1: What Are the Main DTT Capabilities Associated with Enhanced SupplyChain Resilience? Do These Vary Across Different Resilience Stages?

The review shows that DTT affects supply-chain resilience differently across four stages: preparedness, resistance, rebound, and growth. At the preparedness stage, DTT improves the ability of firms to anticipate disruptions and to design robust networks before an event occurs. Digital twins integrate real-time data, historical records, and simulation models into a single representation of the supply chain. This representation increases visibility and traceability of material, information, and financial flows. As a result, managers can identify critical nodes, evaluate alternative sourcing and capacity options and test "what if" scenarios in a safe virtual environment. These mechanisms align with the broader benefits reported across the full corpus (see Table 6), including improved monitoring, risk analysis, and time and cost savings in network design.

At the resistance stage, DTT strengthens the capacity of supply chains to maintain acceptable performance while a disruption is unfolding. The continuous data streams that feed a digital twin allow the system to capture deviations from expected behaviour and to trigger early warnings. When a disturbance occurs, the twin can simulate the impact of different mitigation strategies in near real time and support rapid reconfiguration of inventory positions, production schedules and transport plans. These capabilities translate into more effective decision making, faster reaction times and reduced operational losses. Predictive maintenance and condition monitoring, which are frequently reported outcomes of DTT adoption in the wider literature, also contribute to resistance because they reduce the likelihood that internal failures amplify the effects of external shocks.

Rebound refers to the ability of the supply chain to restore target performance after a disruption. DTT contributes to rebound by providing analytical tools to evaluate recovery paths and to estimate time to recovery. Since the digital twin records the full trajectory of the disruption and the responses that were implemented, it allows managers to replay events, assess which actions were most effective and refine recovery plans accordingly. Simulation and optimisation capabilities support the design of alternative recovery strategies that balance cost, service level and sustainability objectives. These features are closely related to the benefits of risk reduction and efficiency improvement. By guiding the selection of recovery options that minimise downtime and resource waste, DTT supports a faster and more economical return to a viable operating state.

The growth stage goes beyond simple recovery and captures the extent to which firms use disruptions and digital investments to build long-term capabilities. Here, DTT acts as a learning infrastructure that accumulates knowledge from multiple disruption episodes and routine operations. Insights from previous simulations and real events can be encoded into new rules, control policies and performance indicators. Over time, this process strengthens dynamic capabilities such as adaptive planning, collaborative problem solving and continuous process innovation. Over time, this contributes to improved decision making, collaboration and sustained efficiency gains, which are also reported across the wider corpus.

Taken together, these findings indicate that DTT is not only a set of analytical tools but an integrating capability that links data, models, and decisions across the four resilience stages. Preparedness is improved through predictive visibility and virtual stress testing. Resistance is enhanced through real-time monitoring, disruption detection, and adaptive control. Rebound is supported by systematic evaluation of recovery paths and by the reduction of recovery time and cost. Growth is enabled by the accumulation of digital knowledge and by the reliable collaboration and data-driven routines. Across the studies that explicitly connect digital twins to resilience stages, these capabilities represent the core mechanisms through which DTT reinforces supply-chain resilience in a cumulative and path dependent manner.

5.2. RQ2: What Are the Additional Benefits Achieved Through DTT Adoption?

Across the full set of 89 articles, DTT adoption is associated with a broader set of benefits beyond the resilience stage-specific mechanisms discussed above. These benefits are frequently reported in supply-chain contexts characterised by complexity and uncertainty and include enhanced real-time monitoring and decision support, predictive maintenance and condition monitoring, improved risk analysis and disruption prediction, and time and cost savings through more efficient network design and process optimisation. In addition, many studies highlight improved collaboration and information sharing across supply-chain actors, supported by the integration of data and the creation of a shared operational picture. Collectively, these benefits suggest that DTT can deliver both operational performance improvements and managerial decision support that complement resilience outcomes, even when resilience is not explicitly theorised as a multi-stage process in every study.

5.3. Answers to RQ3: What Are the Challenges/Barriers When Adopting DTT for Enhanced Resilience?

Our findings highlight that, while DTT offers numerous benefits at the SC level, it also has significant shortcomings, particularly when it comes to its integration with AI and IoT technologies. These lead to sizeable obstacles to its adoption by industry. Other highlighted issues relate to weaknesses when integrating DTT with legacy digital systems, as well as data standardisation, data management, and data security. Other issues mentioned in the literature include the need to update outdated IT infrastructure, connection issues, data privacy issues related to business-sensitive data, and the absence of a standardised modelling methodology. The high implementation costs, need for high processing power and storage requirements, and the complexity of its design are among the key obstacles that are anticipated to impede the growth of the digital twin application in SCM. The cost of implementing DTT solutions is high and requires large investments in infrastructure creation, infrastructure maintenance, data quality monitoring, and security measures, often across independent businesses with sometimes conflicting competitive objectives. As such, the widespread adoption of DTT is anticipated to continue remaining slow while its fixed and variable costs remain high, alongside its dependence on complex digital infrastructures.

To address these challenges, firstly, supply-chain managers and DT developers need to establish a harmonised data integration policy, which includes a data regulatory framework to standardise data and ensure data consistency throughout the supply chain. Utilising data integration interfaces and data integration platforms ensures seamless switching of data between different stakeholders and different systems. In addition, investing in a scalable and secure cloud infrastructure can enhance data processing capabilities and ensure data privacy. Secondly, combining DTT with other emerging technologies such as blockchain, 5G, RFID, and IoT has the potential to enhance data confidentiality and real-time data transmission. Investing in robust data collection methods, sensor calibration, and real-time data synchronisation would improve the accuracy of DTT simulation models. Finally, DTT requires investment in and cultivation of high precision technical talents to enhance the potential for optimisation of simulated systems. This would lead to the establishment of a more dynamic supply-chain optimisation model in real time, to reflect the entire supply-chain operation, rather than discrete events or network nodes.

5.4. Conflicting Evidence and Boundary Conditions

Although the reviewed studies broadly agree that digital twins can support supply-chain resilience, the evidence base varies substantially in both strength and form, which affects how far the findings can be generalised. Many publications are conceptual, simulation based, or method development studies rather than evaluations of fully operational digital twins, meaning that resilience effects are frequently inferred from improvements in visibility, prediction, or decision support instead of being measured through explicit resilience metrics. In addition, reported effectiveness is often dependent on enabling conditions such as data availability, interoperability across organisations and systems, and continuous data flows supported by IoT, platform integration, and sound data governance. Studies that assume timely, high-quality data and strong integration tend to make stronger capability claims than studies that highlight fragmented data, limited cross-organisational coordination, or partial implementation. Generalisability is also shaped by sector concentration, because detailed demonstrations are more common in food retail, semiconductors, and humanitarian logistics, and may not transfer directly to industries with different regulatory environments, asset characteristics, or network structures. Finally, the term digital twin is used inconsistently across studies, ranging from episodic discrete event simulation models for scenario testing to continuously updated operational twins, and this difference influences which capabilities are realistically achievable. For these reasons, several capabilities, especially those associated with rebound and growth, should be treated as promising but still emerging propositions that require longitudinal studies and implementation-focused empirical validation.

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In addition to these boundary conditions, the literature implies several common implementation failure modes, even though unsuccessful projects are rarely reported in detail. Digital twin initiatives can underperform when data sources are incomplete or inconsistent, when interoperability between enterprise systems and partners is limited, or when models cannot be maintained as processes and network configurations change over time. Organisational constraints also matter, including limited analytical skills, unclear ownership of the twin, and insufficient governance for data sharing and decision rights, which can prevent the twin from being trusted or used in operational decisions. Cyber security and commercial sensitivity can further restrict data access and limit cross-organisational integration, reducing the feasibility of end-to-end twins in practice. These issues suggest that reported benefits may be subject to publication bias and that the absence of negative case evidence should not be interpreted as the absence of failure risk.

5.5. Dynamic Capability Explanation of Stage-Specific DTT-Enabled Resilience

Digital-twin-enabled resilience capabilities can be interpreted through the dynamic capability view (DCV) as shown in Figure 9, which explains how firms build, integrate, and reconfigure resources to address changing environments. In this review, DTT is treated as a bundle of digital resources that combines data integration, modelling, and decision support. These resources do not generate resilience automatically. Rather, they strengthen resilience when they are embedded in dynamic capabilities that enable sensing, seizing, and reconfiguring across the disruption timeline.

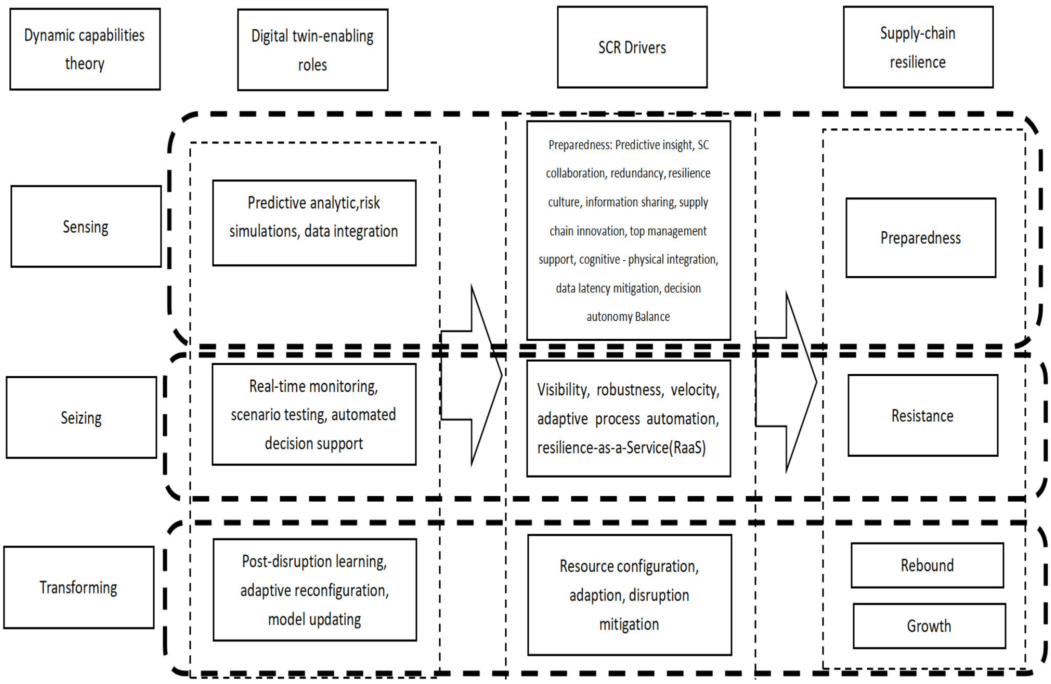

Figure 9. Digital twins enable supply-chain resilience under DCV.

In the preparedness stage, digital twins primarily support sensing. By integrating multi-source data and maintaining a current representation of network states, DTT strengthens end-to-end visibility, early warning, and predictive risk analytics. Virtual stress testing further extends sensing by enabling the exploration of disruption scenarios and vulnerability identification before events occur. These sensing-oriented mechanisms explain why preparedness capabilities are frequently emphasised in conceptual and modelling studies, where improved visibility and prediction can be demonstrated even without full-scale operational deployment.

In the resistance stage, digital twins support seizing through time-sensitive decision making and coordinated execution. Real-time disruption detection and anomaly recognition enable rapid interpretation of unfolding conditions. Adaptive control and data-driven coordination allow organisations to select and enact response options that stabilise performance, for example by adjusting inventory policies, production schedules, or logistics routes. Under DCV, these seizing mechanisms depend on decision rights, process integration, and interoperability, which helps explain why evidence is stronger in contexts with mature data infrastructure and cross-functional coordination.

In the rebound stage, DTT contributes to reconfiguring by supporting recovery planning and resource redeployment. Predictive recovery modelling and recovery path evaluation allow organisations to compare restoration alternatives under constraints and to allocate resources more effectively. Resource reconfiguration support and workflow automation represent more advanced reconfiguring mechanisms that require deeper integration of the twin with operational systems and organisational routines. This helps explain why rebound stage capabilities are often presented as emerging propositions and are less frequently validated in longitudinal, real-world settings.

In the growth stage, digital twins support learning and renewal, which are central to sustained dynamic capabilities. Post-disruption analysis and the codification of disruption experience into models and routines contribute to capability development and strategic redesign. This extends resilience beyond recovery by enabling firms to update policies, redesign network structures, and institutionalise data-driven practices. The DCV perspective therefore clarifies why growth stage claims are highly contingent on governance maturity and sustained investment, and why empirical evidence remains limited relative to earlier stages.

Overall, the dynamic capability view provides an integrative theoretical explanation for why digital twins can generate different resilience capabilities across stages. Preparedness and resistance align more directly with sensing and seizing mechanisms, which are more readily demonstrated in existing studies. Rebound and growth rely more heavily on reconfiguring and learning mechanisms, which require deeper organisational embedding and therefore show more variable evidence across contexts.

6. Future Research Opportunities

Our analysis revealed recent advancements in DTT research within the supply-chain resilience area, summarising the benefits of DTT adoption and emphasising its associated potential risks and challenges. Strategies to address these challenges are also proposed. Given the emerging nature of DTT adoption at the SC level, research opportunities are abundant, and there are numerous areas for future research to focus on. For example, DTT cannot be used in isolation; research on how DTT can integrate with other technologies, enhance human–machine collaboration, and explore DTT applications in the area of supply-chain resilience would be very worthwhile. Considering that one of the key characteristics of DTT is the large volume of data communication, future research on data security and data interoperability would also be valuable. Due to the emerging and evolving technological development of DTT, this research reflects its uncertainties and ambiguities. Therefore, future research directions can be summarised as follows:

6.1. DTT and Resilience

The 89 articles reviewed show that digital twins are increasingly discussed in supply-chain contexts characterised by risk, disruption, and robustness concerns. However, only a minority explicitly frame their contributions in terms of "supply-chain resilience" using formal resilience definitions or multi-stage frameworks. In many studies, resilience-related outcomes appear indirectly through concepts such as risk reduction, vulnerability assessment, continuity planning, or flexibility, without being theorised or measured as resilience in its own right. Future research could therefore develop dedicated theoretical and empirical work that explicitly conceptualises digital twins as resilience capabilities, adopts established resilience constructs and metrics, and examines how digital-twin-enabled mechanisms affect resilience across preparedness, resistance, rebound, and growth stages.

6.2. Human–Machine Collaboration

With digital twin models increasingly become more powerful, studies into how humans/managers can use the resulting information to make better decisions based on insights and recommendations generated by DTT are scarce. This is particularly true when DTT is integrated with AI technologies. DT in SCR heavily relies on AI and machine learning for data analysis and decision support. However, human expertise remains crucial for tasks requiring judgment, intuition, and understanding of the broader business context. Investigate how human expertise and decision-making can be effectively integrated with AI and machine learning algorithms is key to unlock DTT's full potential. This could involve research on user interface design, trust, and transparency in AI-powered recommendations, and the development of collaborative workflows for managing complex supply-chain scenarios [59].

6.3. Ethical Implications of DTT

As with any data-driven technology, DTT raises ethical concerns. Analysing the potential ethical concerns surrounding DTT adoption in SCR is essential for its responsible implementation. Data privacy, algorithmic bias, and the impact on job displacement within the supply-chain workforce are critical issues that demand careful examination Research in this area can explore strategies to mitigate these concerns, ensuring responsible data governance and fostering ethical considerations throughout the design and implementation of DTT SC systems.

6.4. Cybersecurity and Interoperability

Our study highlighted that while investigative approaches to enhance the security and interoperability of DT in SCR platforms should be a key research avenue, contributing to the overall increased supply-chain security [28], studies in this area remain scarce. Researchers should further examine standardised data formats required, secure communication protocols, and robust cybersecurity measures to protect against cyberattacks and data breaches within a digital twin supply chain.

6.5. DTT and Supply-Chain Sustainability

Our SLR findings suggest that major efforts in researching DTT adoption in SCs have been mainly focusing on the economic benefits of DTT. However, given DTT's potential role in supporting the whole life cycle management of a product/service across end-to-end supply chains, it has also great potential to supporting the adoption of more sustainable practices such as circular economy and NetZero, and support innovative concepts such as digital product passports further aimed at enhancing the sustainability of supply chains. Researchers could examine how to use DTT for reduced environmental impact, monitoring resource consumption and waste generation, and designing DTT-enabled sustainable supply-chain models that factor in environmental and social sustainability metrics.

6.6. Integration of DTT with Other Technologies

Aside from the above potential future research directions highlighted, one major theme that emerged from our study is the need for DTT to better integrate with innovative technologies, such as blockchain, 5G networks, IoT, Robotics, Virtual Reality, Augmented Reality, and Artificial Intelligence. The integration of these technologies could significantly improve the accuracy and reliability of digital twin simulations and provide stakeholders with more comprehensive insights into their supply-chain operations. For example, combining blockchain with digital DTT can increase the security and privacy of supply-chain data, guaranteeing that data is tamper-proof and openly available to authorised parties. Furthermore, the 5G network and IoT technologies can improve real-time data gathering and transmission, allowing stakeholders to monitor and respond to problems in their supply chains in real time. Robotics, virtual reality, and augmented reality may potentially play a role in improving the accuracy and realism of digital twin simulations and allowing stakeholders to experiment with different situations in a virtual environment. Research in this area remains in its infancy though.

7. Conclusions

Research on digital twins in supply-chain resilience remains emergent. Across the reviewed literature, several findings are well supported. First, digital twins are consistently discussed as strengthening supply-chain decision making through improved visibility, monitoring, and modelling of network behaviour under uncertainty. Second, the most frequently reported adoption barriers relate to data availability and quality, interoperability across systems and partners, and the organisational capabilities required to maintain reliable data flows and governance.

Our stage-based synthesis indicates that digital twin capabilities can be aligned with different resilience needs, but the strength of evidence varies by stage. Based on the subset of studies that explicitly link digital twins to resilience constructs and provide sufficient detail for classification, preparedness is most often associated with end-to-end visibility, predictive risk analytics, and scenario or stress testing. Resistance is most often associated with real-time disruption detection, adaptive control, and data-driven coordination. Rebound is most often associated with recovery modelling and evaluation of alternative recovery paths. Growth is most often associated with post disruption analysis, capability development, and strategic redesign. However, many studies remain conceptual or simulation-based and do not directly measure resilience outcomes, so these mechanisms should be interpreted as indicative rather than definitive.

Finally, several promising propositions require further empirical validation. In particular, rebound and growth-related claims such as workflow automation, sustained organisational learning, and long-term capability accumulation is less frequently examined in real-world and longitudinal settings. Future research should prioritise implementation focused and cross-sector studies that operationalise resilience metrics, test boundary conditions such as integration maturity and data governance, and evaluate how digital twins contribute to resilience outcomes over time.

7.1. Theoretical Contributions

This review contributes to theory in two ways. First, it consolidates fragmented evidence on digital-twin-related benefits, barriers, and reported implementation considerations in supply-chain contexts affected by risk, disruption, or uncertainty. Second, it advances stage-based resilience theorising by mapping digital twin capabilities to preparedness, resistance, rebound, and growth, thereby clarifying when particular mechanisms are most frequently discussed and where evidence remains limited. The addition of the growth stage highlights post-recovery learning and strategic redesign as an emerging area of interest in the digital twin resilience literature.

Compared with prior reviews that primarily focus on defining digital twins, describing enabling technologies, or discussing digitalisation and resilience at a general level, this review provides a capability-focused, stage-differentiated synthesis. Specifically, it distinguishes digital twin capabilities as mechanisms from reported benefits and outcomes and from adoption barriers, and it transparently separates the broader evidence base from the subset of studies that provide sufficient stage-specific detail for classification. This positioning clarifies what is well supported across studies and what remains contingent or under evidenced, particularly in rebound and growth stages.

7.2. Practical Implications and Limitations

For managers, the synthesis provides a structured view of where digital twins are most often discussed as useful across resilience stages, and which enabling conditions and barriers are most commonly reported. This can support prioritisation decisions on use cases, data integration requirements, and governance arrangements before large-scale investment.

This study has several limitations with implications for interpretation. First, although a systematic review process was employed, some relevant studies may not have been retrieved due to database coverage, indexing, and English-language restrictions, which may bias the sample towards well-represented outlets and regions. Second, only a subset of the included articles provided sufficient stage explicit detail for classification. Although the remaining studies informed the benefits and barriers synthesis, the stage-based capability map may underrepresent mechanisms that are discussed without temporal specificity. Third, many studies were conceptual or simulation-based rather than evaluations of operational digital twins, meaning that resilience impacts are often inferred from improvements in visibility or decision support rather than measured through explicit resilience metrics. Finally, implementation failures are likely underreported in published research, so the absence of negative case evidence should not be interpreted as absence of failure risk. As the field is developing rapidly, new implementations may also emerge after the review cutoff date.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/su18052361/s1, PRISMA_2020_checklist [110], PRISMA_2020_abstract_checklist.

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